THE ALTMAN CORPORATE FAILURE PREDICTION MODEL: APPLIED AMONGST SOUTH AFRICAN MEDICAL SCHEMES

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Declaration

I hereby declare that this paper constitutes my own work and that through extensive literature research; ideas, expressions, writings or findings of others have been incorporated, for which appropriate credit has been given.

Signature ………………………………………………

Fanelo James Arens

ABSTRACT

THE ALTMAN CORPORATE FAILURE PREDICTION MODEL: APPLIED AMONGST SOUTH AFRICAN MEDICAL SCHEMES

This study has a number of interrelated objectives that seek to understand and contextualize the Altman bankruptcy prediction model in the setting of the South African medical schemes over a ten year period (2002 to 2011). The main objective of this study is to validate the Altman Z_2 model amongst the medical schemes in South Africa; in terms of accurately classifying Z_2-scores of ≤ 1.23 and ≥ 2.9 into the a priori groups of failed and non-failed schemes.

The average classification rates in the period 2002 to 2011 are as follows: 82% accuracy rate and 17.9% error rate. A linear trend line inserted in the graph shows the accuracy improving from 72% to 91% between the period 2003/2004 to 2011/2012.

This outcome is consistent with the conclusion in previous studies (Aziz and Humayon, 2006: 27) that showed the accuracy rates in most failure prediction studies to be as follows: 84%, 88%, and 85% for statistical models, AEIS models and theoretical models respectively.

Although this study validated the Altman model, further studies are required to test the rest of the study objectives under conditions where some of the assumptions are revised.

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By

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1. Introduction

South African (SA) medical schemes constitute a significant sector of the economy in terms of the number of schemes as well as the reserves under management. As at 31 December 2011 “there were 97 medical schemes (26 open and 71 restricted), representing a total of 8 526 409 lives” (Council for Medical Schemes (CMS) annual report, 2011: 114). In 2011 schemes managed a total combined fund of R36.8 billion, 13% higher than 2010.

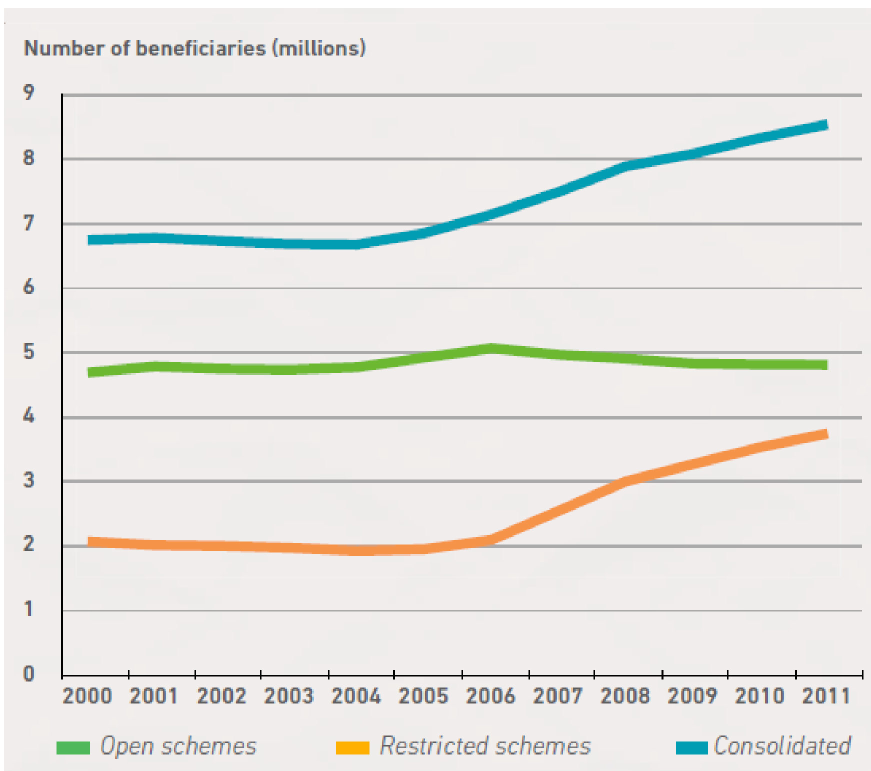
Medical schemes operate as not for profit organizations regulated under the Medical Schemes Act, No. 131 of 1998. There has not been any significant change in the competitive structure as well as service delivery model of this sector since the birth of democracy in South Africa. The sector and the entire health care industry have thus not delivered on the national aspirations of achieving equitable and affordable health care for all South Africans. This realization has driven the ruling party and South African government to consider an alternative healthcare funding and delivery model in the form of National Health Insurance (NHI), which is in its advanced stages of conceptualization and early stages of implementation. The NHI will in all likelihood expedite an unprecedented consolidation in the medical scheme sector that will result in a few surviving schemes that sell augmented services not provided for in the NHI benefit structure.

This section will provide a background to the problems the medical scheme sector is currently facing, which are: failure of significant growth in membership, high medical inflation and its contributing factors, the high burden of disease in South Africa, the competitive structure of the private health care industry as well as the role of the solvency ratios as a tool to monitor schemes’ capital adequacy.

1.1. Failure of significant membership growth amongst SA medical schemes

Membership growth of medical schemes remained stagnant between 2000 and 2004 (**Exhibit 1**). The growth observed between 2005 and 2011 was in the restricted schemes (employer schemes) whilst there was a decline in numbers in open schemes (CMS annual report, 2011: 114). The Government Employee Medical Scheme (GEMS), which is a restricted scheme, largely accounted for this growth. During this period (2005 to 2011) the number of beneficiaries grew from just under 7 million to around 8.5 million.

Exhibit 1: Trend in number of beneficiaries on medical schemes (2000 to 2011)



CMS Annual Report (2011: 114)

Open schemes showed negative growth between 2006 and 2011. This trend could be because open schemes are voluntary and are therefore susceptible to loosing members during difficult economic times as experienced in the period 2007 to 2011. Medical schemes spend a significant amount of money on marketing. In 2011 the brokerage costs (for all schemes) was R1.4 billion; a 5% increase from 2010 (CMS annual report, 2011: 134). Despite these exorbitant marketing fees, there has been no significant growth in total membership of the sector over the last ten years.

1.2. High medical inflation and its contributing factors

High medical inflation is one of the main factors contributing to the failure of the private health care system in South Africa. The current private health care financing system is the root cause of the runaway inflation. Aragua and McIntyre (2012: 1) observed that the South African health care system has "an overall progressive financing system but a pro-rich distribution of health care benefits". The above authors lament that the South African private health care system mainly covers a small portion of the population that is mainly rich (Ataguba & McIntyre, 2012: 1). The authors observe that this small rich group that benefits the most from the health care system has the lowest share of the disease burden. The above observation has major implications for our healthcare system and the sustainability of medical schemes in the private environment. It in effect means that the current healthcare system is inequitably accessed and that resources are, as a result, inequitably distributed. The behaviour of suppliers is typically influenced very strongly by the incentives created by the payment mechanism in the health care system (Mackintosh, 2003: 19). The current healthcare system is to a large extent supply based rather than needs and demand based. High income health care systems, such as is found in South Africa, have strong commercial elements on the supply side (Mackintosh, 2003: 17). Service providers such as specialist are the main drivers of the supply side. This may present a conflict of interest on the part of the service providers who are in a position to prescribe a healthcare intervention from which they are likely to derive economic benefits.

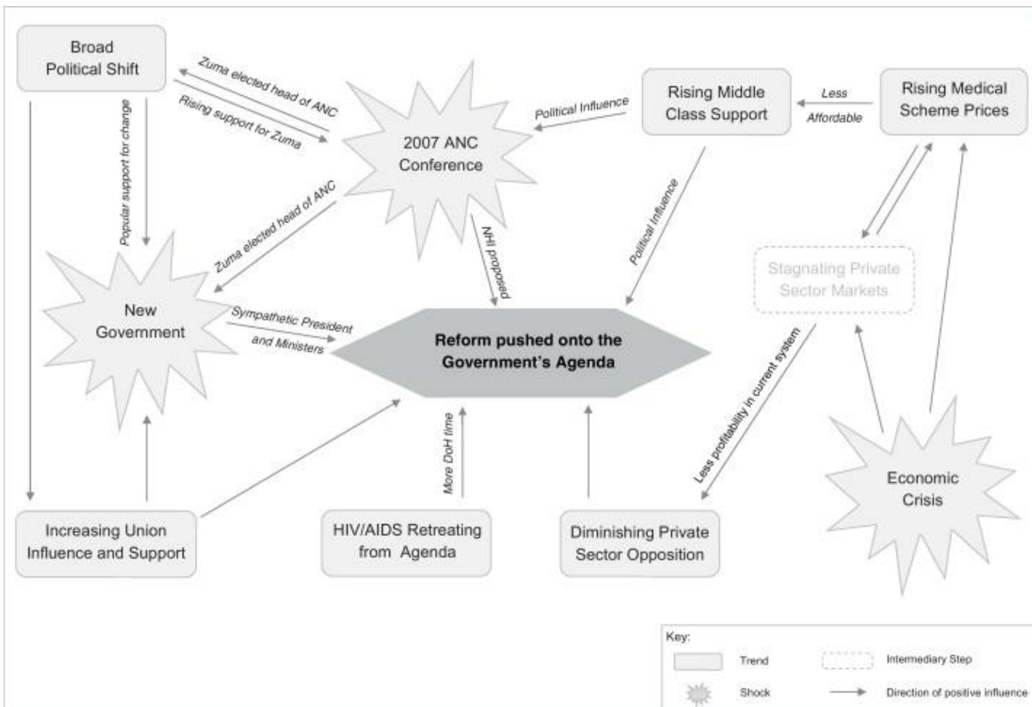
The medical scheme sector has ninety seven individual schemes (as at 2011), all of which provide very similar products. There is often no distinct value differentiation amongst the schemes and options. Individual schemes, some of which are very small, are often not in a position to negotiate competitive tariff rates with the large South African hospital groups, which are displaying the characteristics of an oligopoly (Germishuizen, 2009: 38). Medical schemes are therefore price takers whilst hospitals are price setters.

Medical schemes are also under pressure from substitute products like hospital plans offered by mainstream insurance companies. The products are often competitively priced as they are not governed by and exposed to the risk of prescribed minimal benefit (PMB) legislation (Medical Scheme Act (MSA) 131 of 1998), which prescribes that schemes have to pay in full (at the price quoted by the service providers) for all PMB conditions. The PMB legislation poses a major risk to medical schemes as the provisions of the legislation lend themselves to abuse by service providers. According to the Towers Watson survey report (2012: 6) the top three global healthcare cost drivers are medical technology cost (52%), overuse of healthcare by service providers (50%) and profit motive of service providers (31%) in that order.

In addition to the PMB legislation, medical schemes can no longer choose their members or discriminate against members on the bases of claiming patterns, disease profile or family size. Survival of medical schemes is therefore dependent upon the skill and technology the medical scheme possesses to mitigate claims risk. It has been established, that “the number of chronic beneficiaries in a family is an important risk factor if a member is classified into a normal claiming category or an above-normal claiming category” (De Villiers, Van der Merwe & Van Wyk Kotze, 2004). In addition to the skill and technology mentioned above, there needs to be definitive efforts, such as disease management programs that specifically address specific disease burdens as well as compliance to medications and treatment plans. Smaller schemes are not always in a financial position to afford these risk mitigating measures. Even for those that can afford them, the success of these measures are not always easily discernible and quantifiable, hence scheme executives do not always regard them as priority.

Healthcare cost is one of the factors that necessitated the government to consider alternative healthcare funding and delivery methods. In their study, Pillay & Skordis-Worrall (2013: 326) identified certain factors that could have determined the agenda setting process for healthcare reform in South Africa such as: “a change in government, increase in the cost of private medical schemes, and increase in support for reform from various stakeholders”. The framework below (**Exhibit 2**) illustrates all other contributing factors in the policy agenda setting process.

Exhibit 2: Health care reform agenda setting process in South Africa



Source: Pillay & Skordis-Worrall (2013: 326)

Medical schemes have been casualties of this escalating healthcare cost, with a number of schemes having had to close down or merge into other schemes. The private healthcare cost is indeed essential in this framework as it is likely to undermine any government initiatives to attaining equitable and affordable healthcare for all South African citizens. Hence all government efforts are targeted at containing the escalating healthcare costs and this, in government’s view, will finally be achieved by the introduction of the National Health Insurance (NHI) (Dept. of Health, South Africa, 2011: 32).

It does appear at this stage that the NHI will play a significant role in both the financing and provision of health care. The role of medical schemes in the financing of healthcare has not been well elucidated by the authorities thus far. Some antagonists of the NHI feel that the susceptibility of the healthcare system to regulation presents an opportunity for policymakers to “achieve social protection objectives through the strategic management of markets rather than exclusively through less responsive systems based on tax funded direct provision” (van den Heever, 2012: 12).

1.3. High burden of disease in South Africa

The Lancet Special Report (2009: 4, 5) highlights the major healthcare challenges and pressures also known as the burden of disease. The following are the elements of the so called Quadruple Burden of Disease, according to the Lancet report (2009), currently plaguing the South African health care system:

(i) Maternal, newborn and child health: 1% of global burden (2–3 x average for comparable income countries)
(ii) Non-communicable disease: < 1% of global burden (2-3 x higher than average for developing countries)
(iii) HIV/AIDS and Tuberculosis (TB): 177% of HIV global burden (23 x global average) 5% of global TB burden (7 x global average)
(iv) Violence and injury: global burden of injuries (2x global average for injuries per capita, 5 x global average homicide rate)

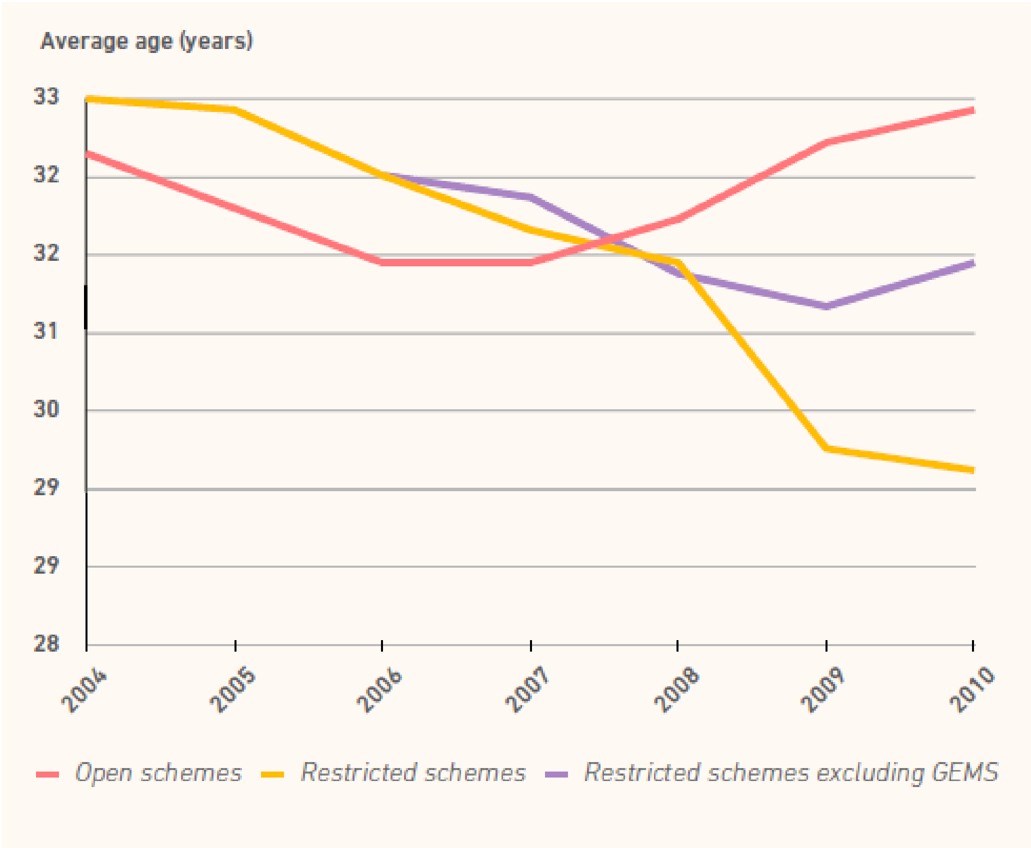
The above categories of disease burdens are way above global averages of peer countries, particularly Human Immunodeficiency Virus / Acquired Immunodeficiency Disease (HIV and AIDS) and TB. SA has shown no progress in reaching the Millennium Development Goals (MDGs) and has instead regressed in some of the goals (The

Lancet 2009: 4, 5). It is important to note that most countries have only one or at most two categories of Burden of Disease compared to SA which owns four; hence the quadruple burden of disease.

1.4. Aging of the medical scheme population

Members of open schemes have demonstrated a significant aging pattern from 2007 to 2010 (**Exhibit 3**). There are a number of factors that has led to this trend. The life span of the general population has increased as a result of the life-saving medicines introduced to the South African market in the past twenty years. The success of the Antiretroviral (ARV) treatment program has also played a significant role in curbing unnecessary morbidity and mortality from HIV and Aids. Open schemes are more vulnerable to the above phenomenon as the age of restricted scheme members is influenced and limited by the retirement age of the working population.

Exhibit 3: Aging trend in medical schemes of SA



Source: CMS Annual Report, (2011: 159)

1.5. Product

There is very little differentiation in the products available to potential medical scheme members, as all schemes offer very similar products. The options within the schemes range from low cost: which mainly cater for PMBs to high-end: offering more benefits in categories such as chronic medicines for non-PMB conditions, optical and dental benefits as well as higher specialist fees. The problem medical schemes face is that there is no real tangible value offering that differentiates one scheme from the other. This makes it easy for members to switch scheme once they encounter a situation where another scheme seems to reimburse better for the condition that they intend claiming for in the near future. Some of the competitive strategies employed by medical schemes are product augmentation with supplementary services such gym memberships and discounts on other insurance products. The MSA 131 of 1998 clearly defines the business of a medical scheme and hence most schemes are unable to form the above strategic partnerships.

1.6. Porter's five forces competitive model: in the health care industry

Analyzing the medical scheme industry using the Porter five forces competitive model clearly illustrates the structural problems in the industry; and perhaps also hints that these problems are unlikely to be resolved to any degree by market forces. The following are the elements of the Porter model that will be briefly described in the context of the SA medical scheme and health care industries:

- Threat to new entrants
- Threat to substitution
- Bargaining powers of suppliers
- Bargaining powers of customers

1.6.1. Threat of new entrants

Since medical schemes are not for profit organization, their capital is derived from membership contributions. The establishment of such organizations has been easy in the past, with no real barriers to entry; hence the high number of medical schemes in the country in earlier years. Since medical schemes are strictly governed by the Medical Schemes Act 131 of 1998, their business models are similar and in the public domain. In recent years, solvency levels have been dropping, dipping below the target figure of

25%. Because of the protracted high unemployment rates at and above 24% between 2009 and 2011 (Statistics SA. 2011), as well as inability of the schemes to compete on the basis of innovation, this sector has started to become unattractive and hence has not been attracting new entrants in quite a while and instead the number of schemes has been reducing as a result of business failures and mergers (**Exhibit 16**: p58).

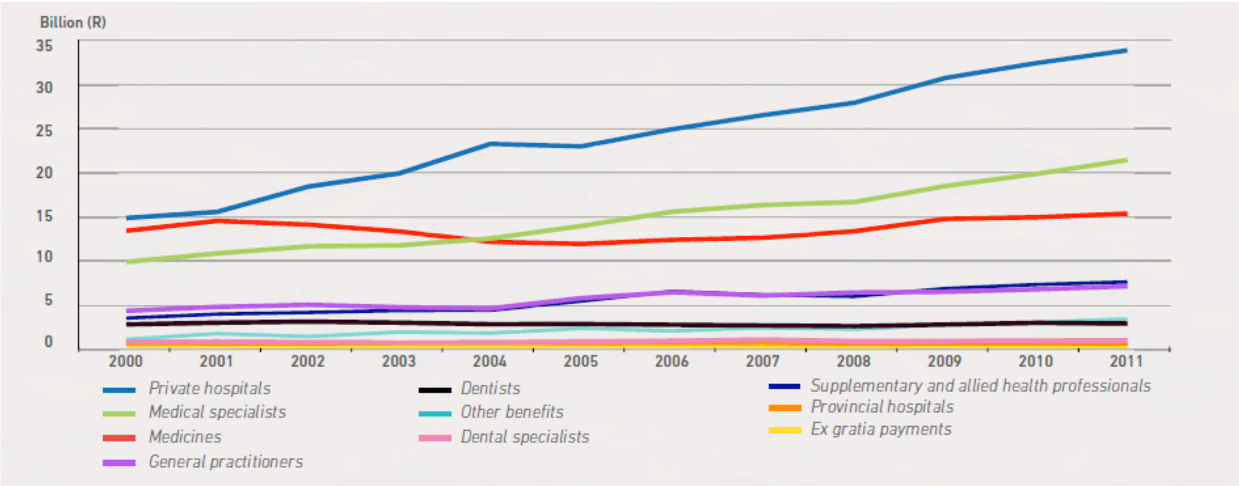
1.6.2. Threat of Substitution

Alternative health insurance products such as hospital plans offered by traditional insurance houses have been a constant threat to the medical scheme sector. There have also been a growing number of insurance products that cover the shortfall between what the service provider charges and what medical schemes pay for non-PMB conditions. These products have the effect that members may buy down to lower options with lessor cover for non-PMB conditions.

1.6.3. Bargaining power of suppliers

Because of the concentration of main suppliers such as the hospitals, with effectively only four big groups (Netcare, Mediclinic, Life Health and NHN), medical schemes don't have any bargaining power and therefore reimbursement tariffs (prices) are dictated by the hospital groups. This is evidenced by the un-abating increase in the private hospital cost portion of medical schemes from 2000 to 2011 as illustrated by the **Exhibit 4** below. Note the sustained growth in hospital and specialist costs from 2000 to 2011. The prices of medicines (red line) abated from 2001 with the introduction of Single Exit Pricing (SEP) to the pharmacy sector. The government has established a commission of enquiry, as of Jan 2014, that will investigate and possibly recommend on the reasons for and solutions to the runaway healthcare costs in South Africa. The commission is expected to finalize its mandate and produce a report by the end of 2015.

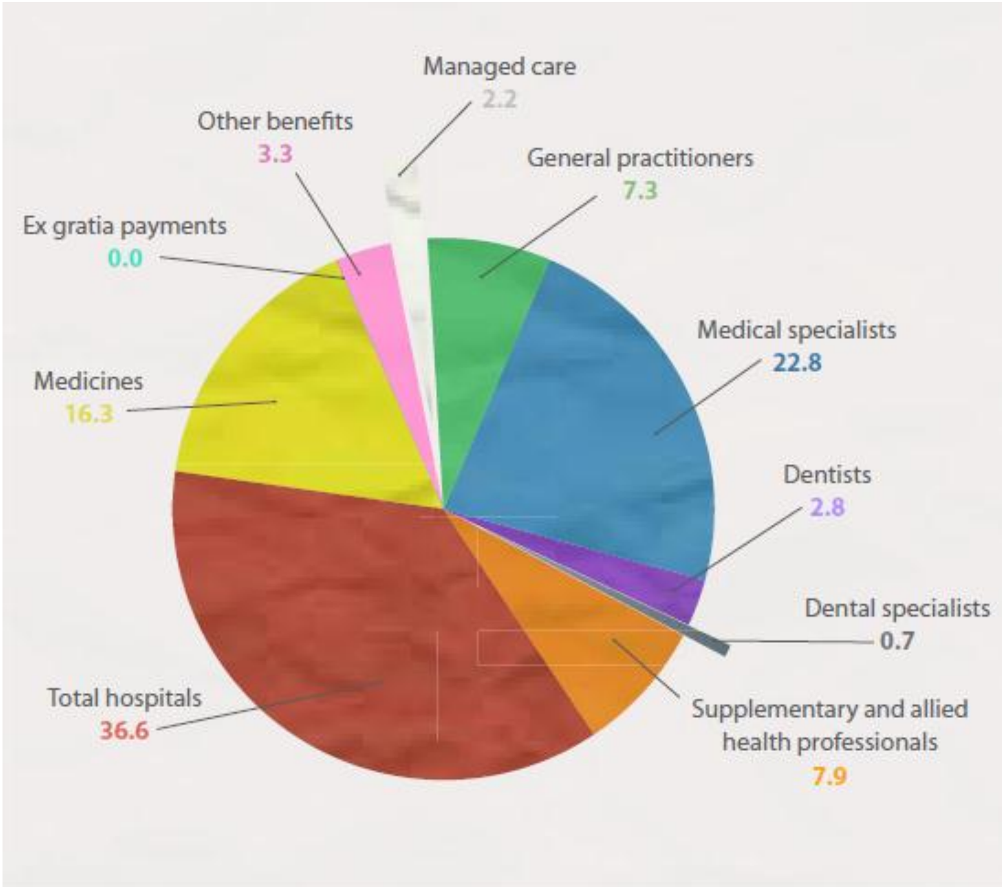
Exhibit 4: Trends in medical scheme costs drivers (from 2000 to 2011)



Source: Council for Medical Schemes (2011/2012: 119)

Specialists are the second biggest category of cost drivers that medical schemes have no control over. This largely emanates from the fact that these suppliers have the unrestricted latitude to prescribe a number of interventions from which they benefit enormously economically constituting a conflict of interest. Specialists also simply charge the member where they are being short paid by the medical schemes (also known as double billing). Hospitals and specialists have an uncomfortably close relationship with each other; a relationship that would not be tolerated by the competition commissions in other industries and other countries. **Exhibit 5** below depicts the proportional representation of the private hospitals and specialists in the cost structure of medical schemes.

Exhibit 5: Major cost drivers in the private healthcare arena (2011/2012)



Source: CMS Annual Report (2011-2012: 116)

Because of this uneven distribution of bargaining power across the industry, as well as the close relationship between hospitals and specialists, it is not surprising that this industry is not responding to normal market forces as other industries do.

1.6.4. Bargaining power of customers

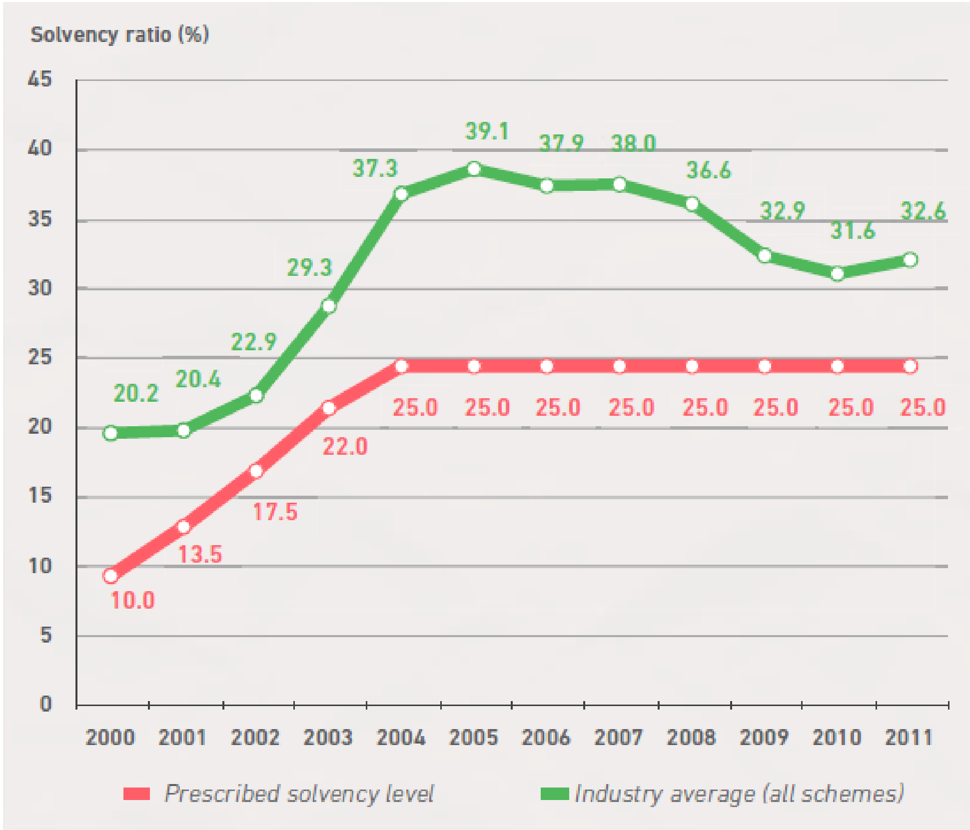
Members are not in a position to negotiate the services they need or the tariffs they deem fair for the services. The problem is asymmetry of information where the technical information about the services to members / patients resides with the medical schemes and service providers. Medical schemes generally negotiate tariffs with private hospitals, against the odds described above. Because of the moral hazard factor introduced by medical insurance, patients are generally apathetic to the cost of the health care they receive. Belonging to a medical scheme “is the most important predictor of using a private provider, particularly for inpatient care” (Alaba & McIntyre, 2012).

Switching costs, associated with moving from one scheme to the other, are so inconsiderable, that members are continually in a state of flux into and out of schemes, a situation that only benefit the brokers.

1.7. Solvency levels of medical schemes

The Medical Schemes Act requires that “medical schemes maintain accumulated funds (reserves) as a percentage of gross annual contribution of not less than 25%” (CMS Annual Report 2011: 142). The main statutory obligation of the CMS is to ensure that schemes at all times remain financially sound at a solvency level of above 25%. Schemes that fall below this level are intensely monitored; which includes regular submission of management accounts, regular meeting of the Principal Officer (PO) and the Board of Trustees (BOT) of the scheme with the CMS, as well as quarterly submissions of business plans. **Exhibit 6** below depicts the prescribed solvency levels in red and the industry averages of all schemes in green. Of note is that the average solvency level of all schemes has dropped and remained under the 35% level since 2008.

Exhibit 6: Solvency levels of schemes (2000-2011)



Source: CMS Annual Report (2011-2012: 142)

1.8. Summary of introduction

The medical scheme industry has failed to thrive and to provide competitive products. The main factors stifling schemes growth are the following; failure of the industry to grow members; the aging membership of medical schemes; the unusually high burden of disease in South Africa; high medical inflation; as well as the competitive industry forces that result in lack of responsiveness of the industry to market forces. Failure to grow sales results in the failure to grow reserves. In the current monitoring mechanism of medical schemes, a scheme is deemed to be failing if its solvency ratio is equal to or below the statutory level of 25%. Raath (2010; 29) argues for a risk based monitoring tool which considers the particular risk of each scheme. It is for this reason that this paper explores the possibility of applying the Altman failure prediction model to the medical scheme industry.

1.9. Objective of the study

This study has a number of interrelated objectives that seek to understand and contextualize the Altman bankruptcy prediction model in the setting of the South African medical schemes. The objectives are as follows:

I. To do research of the literature on the subject of corporate bankruptcy prediction models, with a view to establishing what the latest evidence is on the validity of the Multivariate Discriminant Analysis (MDA) models in general and the Altman model in particular.

II. To validate the Altman Z_2 model amongst medical schemes in South Africa in terms of accurately classifying Z_2-scores of ≤ 1.8 and ≥ 2.9 into the a priori groups of failed and non-failed schemes

III. Establishing new Z_2-scores (and limits) through the re-estimation of new coefficients for the original variables (T1 to T5) in the SA medical scheme industry: this will be achieved by rerunning the MDA model for the SA medical schemes using the original Altman variables (T1 to T5).

IV. Establishing alternative Z_2-scores (and limits): Rerunning the MDA model using new (industry specific) variables.

2. Literature review

When a business or an industry fails there is often a lot of speculation as to the causes of such failure. The exact reasons for the failure are often unknown and as a result the same mistakes can be repeated. Business failure prediction models attempt to tackle this problem to the extent that a business tool can be used to monitor and detect early signs of failure. However choosing between these different models for empirical application is not always an easy task (Aziz & Humayon, 2006: 18). Predicting business failure as early as possible is always essential, particularly in periods of financial stress and economic upheaval (Diakomihalis, 2012: 97). Bankruptcy prediction is important for financial information users such as investors, creditors, stakeholders, credit rating agencies, auditors, and regulators (Lifschutz & Jacobi, 2010: 133).

The main purpose of corporate failure prediction is to have a methodological approach which identifies and discriminates companies with a high probability of future failure from those considered to be healthy (Amendola, Bisogno, Restaino et al, 2011: 295). The majority of these studies have been on assessing corporate health “to predict longevity, with less emphasis on the causes of failures” (Holt, 2013: 50).This is one of the criticisms of business prediction failure models, that they seek to predict failure with no sufficient understanding of the underlying causes of failure. For some companies and industries it might be too late for any rescue operations by the time the company is found to fall in the failed category. The counter argument to this is that most of these models predict failure two to five years in advance, providing reasonable time to marshal rescue efforts.

2.1. Possible Causes of Business Failures

In his work on analyzing causes of business failure, Holt (2013: 62) concluded that the generic failure agents (GFA) are shown to be: managerial, financial, company characteristics, and macroeconomic conditions (in order of frequency). The first three reciprocally interact within conditions defined by the latter. Each GFA has a number of sub-causal agents (SCA) associated with it (Holt, 2013: 60). Holt suggests that "innovation can potentially mitigate GFA and SCA negatively or positively" (Holt, 2013: 60).

Exhibit 7 below ranks the GFAs based on percentage of frequency; illustrating that managerial causes of business failure contribute the most at 45% followed by financial causes at 42%.

Exhibit 7: GFA ranking table

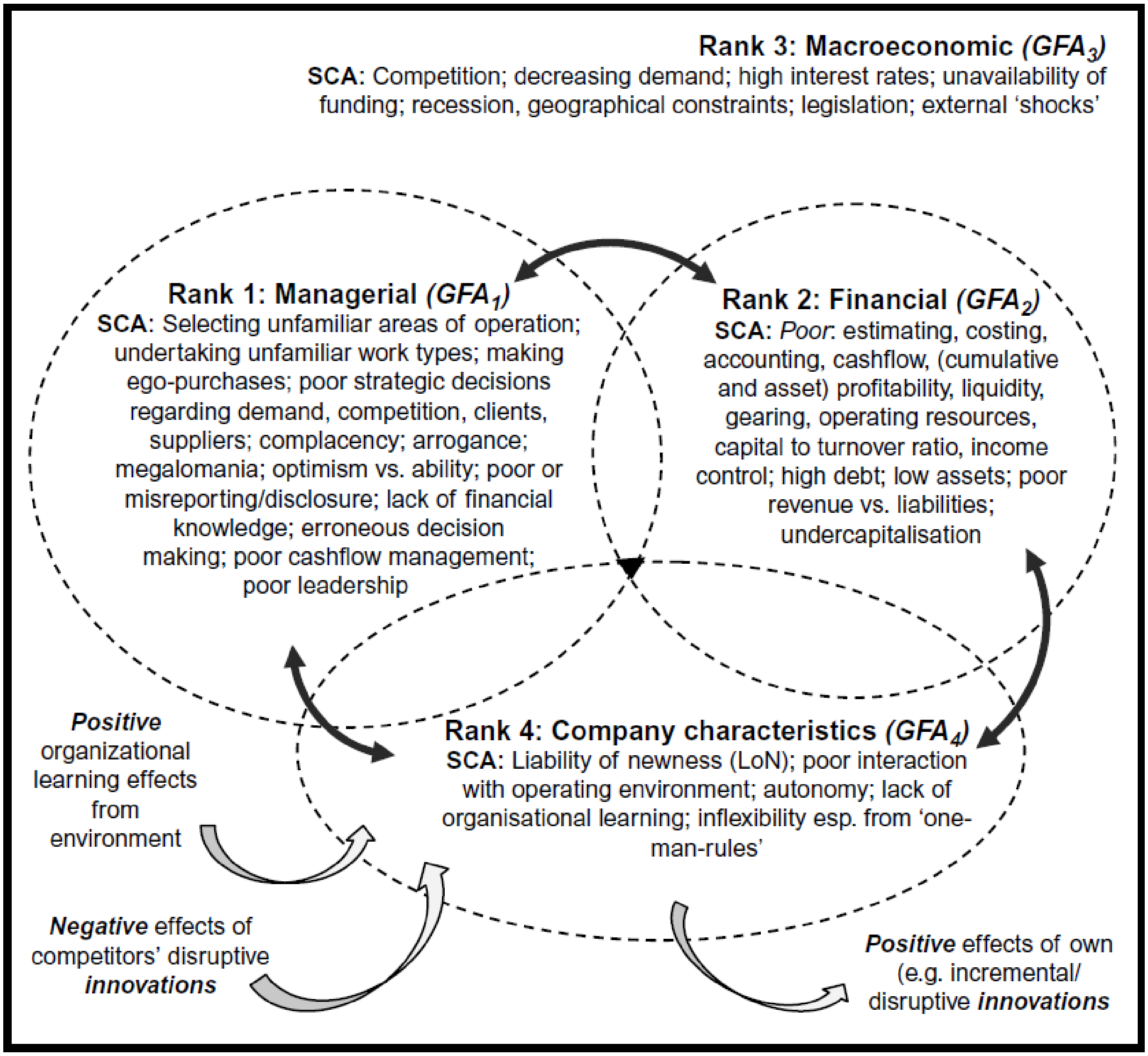
GFA	All literature	
	%	Rank
Managerial	45	1
Financial	42	2
Macroeconomics	8	3
Company characteristics	5	4

Source: Holt G.D. (2013: 62)

Exhibit 8 below illustrates "the inter-GFA reciprocal influence with the shaded central signifying combined failure susceptibility from all GFA combined" (Holt, 2013: 63). It is important to note that most of the SCAs constitute the five financial ratios in the Altman model which are profitability, liquidity, low asset / high debt, capital turnover ratios, and poor revenue vs. liabilities. In this model, innovation plays an important role in aggravating or mitigating the impact of the GFA/CSAs.

Understanding this model can assist in conceptualizing and implementing turnaround strategies for a company once the company has been categorized as distressed or bankrupt by the Altman failure model. For instance, one of the indicators of financial weaknesses is inadequate working capital amongst other things. Inadequate working capital can be a sign of other problems in the business such poor financial management and procurement strategies. This GFA/CSAs causal agent model also lends support to the criticism that macroeconomic factors are not well represented in most of the earlier bankruptcy prediction models.

Exhibit 8: Model of causal agents (GFA/CSA)



Source: Holt, G.D. (2013: 62)

Holt (2013: 65) suggests broad practical considerations to help negate the potential negative effects of GFA (and respective SCAs). The recommendations suggest mitigating measures according to the particular GFA implicated in the framework. The following is a summarized version of Holt's framework (Holt 2013: 65).

GFA_1 managerial: select work of a type and within geographic areas that offer the organization optimum cost control, maintain up-to-date knowledge on demand, competition, clients and suppliers and sustain positive cash flow. Embracing all of these propositions simultaneously is a function of managerial risk minimization /mitigation.

GFA_2 financial: maintain effective forecasting and accounting functions, closely monitor liquidity, avoid high gearing; achieve appropriate returns on operating resources, control income (which includes effective debtor management), avoid poor revenue versus liabilities and avoid under capitalization.

GFA_4 company characteristics: interact effectively with all aspects of the business operating environment and strive for organizational learning.

GFA_3 macroeconomic environment: maintain a business strategy that mitigates the potentially negative impacts, especially from: increased competition, decreasing price levels, high costs of borrowing, legislation, recession, and any other “shocks”.

2.2. Statistical basis of the earlier business failure prediction models

The fundamental basis of most business failure prediction models is to examine and quantify the independent variables which are effective indicators and predictors of business failure or distress (Altman, 2000: 1). Financial ratios are the key input variables in most of these models. It is the link between financial ratios and statistical techniques that are the essence of statistical bankruptcy prediction modeling.

2.3. Bridging the gap between financial ratio analysis and the more rigorous statistical techniques

Financial ratios are commonly used by accountants, managers and analysts to varying degrees of understanding and consistency. The use of these ratios often pivots around the comparison of companies in the same industry. The information gathered from such analysis is barely helpful in understanding the weaknesses and strengths of a company and is of limited use in analyzing the strategic context of a company. As Edward Altman observed, from the 1960's and more so in the 1990's, "academics seem to be moving towards the elimination of financial ratios as an analytical technique in assessing the performance of the business enterprise" (Altman, 2000: 1). Altman (2000) further observed that these academics have started to employ more statistical techniques in explaining and predicting the performance of corporates, often in ways that financial ratios are unable to do. The drawback of such statistical techniques has been that they have not succeeded in finding their way into everyday business practice. The chasm created by these divergent methods of business analysis has been of concern, as there are merits in both approaches. Hence Altman's question, "Can we bridge the gap between financial ratio analysis and the more rigorous statistical techniques which have become popular amongst academics in more recent years?" (Altman, 2000: 2).

2.4. Univariate vs. Multivariate Analysis models

Edward Altman, who is well recognized for his work in predictive failure models since the 1960's, contributed a great deal to the most used model known as the Z-score, which primarily utilizes financial ratios in the predictive model. One of the original works in the area of ratio analysis and bankruptcy classification was by Beaver (1967), in which his univariate statistical analysis of bankruptcy predictors "set the stage for Altman and other authors that followed" (Altman, 2000: 2). Beaver found that a number of ratios could predict failure in firms for as long as five years prior to bankruptcy (Beaver, 1968: 191). In 1972 Deakin, following up on Beaver's work, utilized the same independent variables used by Beaver in 1968 within a number of multivariate discriminant models (Deakin, 1972). The problem of using financial ratios as mentioned above is inconsistency which may lead to instances of under estimating or over estimating the bankruptcy risk. Altman also has concerns with univariate analysis of financial ratios in bankruptcy prediction models for the reasons that the modeling is prone to faulty interpretation and is potentially confusing. Altman argues that “firms with poor profitability and/or solvency record may be regarded as potentially bankrupt, however because of their above average liquidity, the situation may not be regarded as that serious” (Altman, 2000: 8). Multivariate analysis on the other hand introduces the contentious questions of “which ratios are most important in detecting bankruptcy, what weight should be attached to these selected ratios and how should the weights be objectively established” (Altman, 2000: 9). According to Altman, “the importance of the multivariate discriminant analytical (MDA) remains its ability to separate companies into failed and non-failed entities using multivariate measures” (Altman, 1968: 597).

Four out of the five variables (excluding sales / total assets) considered in the Altman model showed significant differences between the failed and non-failed companies (Altman, 1968: 596). Although the fifth variable (sales / total assets) did not display significant differences between failed and non-failed firms, the significance of its contribution to the model made Altman consider it for inclusion in the model.

2.5. Description of commonly used statistical failure prediction models

The Z-score, used by Altman (1968) in his study of manufacturing firms, uses MDA statistical techniques. MDA in its simplest form is the comparison of two or more independent variables between two entities in order to arrive at two estimates, which are in turn compared for statistically significant differences. Altman describes MDA as a “statistical technique used to classify observations into one or several a priori groupings, dependent on the observed individual characteristics” (Altman, 2000: 9). A prior groupings in this case meaning predetermined groupings such as male and female or medicine ‘A’ and medicine ‘B’, or in the case of this study “failed and non-failed schemes”. The shortcomings of univariate studies is that they only “consider measurements used for group assignments; one at a time” (Altman, 2000: 9). The main advantage of MDA in classification problems is “the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics” (Altman, 2000: 9). The other advantage is that ratios are dealt with holistically; thereby addressing the problem of inconsistency. According to Altman (2000: 9), the discriminant function of the model transforms the individual independent variables into a single discriminant score, or Z-value which is then used to classify the object, where:

V1, V2,…Vn = discriminant coefficients

T1, T2,…Tn = independent variable (Altman, 2000: 10).

T1 is the independent variable such as financial ratios, whilst V1 is the discriminant coefficient calculated statistically by the MDA model (Altman, 2000: 10). These coefficients are important as they are derived from different circumstances depending on the measurement and structure of the different ratios. Different industries are therefore expected to have different coefficients. The implicit assumption is therefore that the Z-score model is generalizable if the coefficients are constituted correctly.

2.6. The Altman Z-score

In determining the Z-score, Altman used sixty six companies from the manufacturing industry, with thirty three of them in the bankrupt group and the other thirty three in the non-bankrupt group (Altman, 2000: 10). The bankrupt firms are the ones that filed for bankruptcy (from 1946 to 1965) under the United States (US) Bankruptcy Act. The non-bankrupt companies where chosen by industry as well by their size. The asset size range of the companies was restricted to between $1 million to $26 million (Altman, 2000: 10). The mean asset size of the non-bankrupt companies was slightly greater than that of the bankrupt firms (Altman, 2000: 10). Altman asserts that “matching the exact sizes of the groups were unnecessary” (Altman, 2000: 10). Total asset size being the denominator in the Altman model, doesn’t seem to have biased the bankrupt firms negatively (with smaller total assets); if anything, it would have been a mitigating factor for smaller firms. The financial data of the bankrupt and non-bankrupt companies were from the same period.

In the original Altman study (1968: 594), twenty two potentially helpful financial ratios where compiled for evaluation, which were classified into five ratio categories; liquidity, profitability, leverage, solvency and activity. To arrive at the final five profiles of variables, Altman (1968: 594), followed the following procedure; (i) observation of the statistical significance of various alternative functions, including determination of the relative contributions (by way of the coefficients) of each independent variable, (ii) evaluation of inter-correlations amongst the relevant variables (iii), observation of the predictive accuracy of the relevant variables and (iv) judgment of the analyst. Altman (1968) finally settled on the following variables and profile:

$$Z = 0.012T1 + 0.014T2 + 0.033T3 + 0.006T4 + 0.999T5$$

Where;

T1 = working capital / total assets

T2 = retained earnings / total assets

T3 = earnings before interest and taxes / total assets

T4 = market value of equity / book values of total liabilities

T5 = sales / total assets

Z = overall index (Z-score)

2.7. Descriptions of the ratios used in the Altman Z-scores

From a total number of twenty two ratios put into the Altman model, only five were found to be of discriminant value in confirming the a priori groups of companies. Altman describes the ratios used in his model as follows (Altman 1968: 594):

T1 = working capital / total assets. This ratio describes the net liquid assets of a firm relative to its total capitalization. Working capital is the difference between a firm's currents assets and current liabilities. In a loss making firm, this ratio will consistently shrink because of: reducing credit extension from suppliers and inability to collect debt both resulting in less sales (besides other reasons such as decreasing demand). On the other hand there is also the consequence of less or no retained earnings posted to the balance sheet hence stagnating total assets.

T2 = retained earnings / total assets. This ratio measures cumulative profit over time in relation to total assets. Younger firms will have a smaller ratio compared to older firms that will have had enough time to accumulate earnings. This is consistent with real life observation that new firms are at a higher risk of bankruptcy

T3 = operating profit / total assets. By dividing the total assets into operating profit, this ratio measures the true productivity of the firm in as far as the earnings potential before the influence of interest and taxes. Firms with a lower earning generating capacity are at risk of bankruptcy. There is collaborative evidence between the ratios when one observes that earning generating capacity will increase the numerator in the above ratio hence increasing that ratio as well, improving the general wellbeing of the firm. Signs of financial distress in a firm can therefore be monitored by observing the trends in these ratios long before the Z-score dips into the danger zone.

T4 = market value of equity / book value of total liabilities. This is one of the debatable ratios in the model, as a number of factors other than the intrinsic value of the firm could affect the market value of the equity. However the relevance of the market value is in the fact that a firm is technically considered bankrupt when the book value of the total liability equals or exceeds the market value of equity. The revised Altman model makes provision for private firms as well, by re-estimating the coefficients of this particular variable. Medical schemes are private not for profit organizations, that do not have a market value of equity as a result. The prediction failure of such firms can therefore be determined from the revised Altman model.

T5 = sales / total assets. The asset turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm’s assets. This ratio “is one measure of management capability in dealing with competitive conditions” (Altman, 1968: 595). Based on the statistical significance this measure would not have appeared at all (as it ranks below 0.001), however because of its unique relationship to other variables in the model, sales / total assets ranks second in its contribution to the overall discriminating ability of the model (Altman 1968: 596). This is not entirely surprising as sales are often the main driver of growth in most forecasting models across most industries. Hence a ratio containing sales as a numerator would rank high in contributing to the overall discriminating ability of the model.

The zones of discrimination that depend on the Z_1 scores are:

$Z_1 > 2.99$ = Safe Zone

$1.8 < Z_1 < 2.99$ = Grey Zone

$Z_1 < 1.80$ = Distress Zone

By observing those firms which have been misclassified by the discriminant model in the initial sample, it is concluded that all firms having a Z-score of greater than 2.99 clearly fall into the "non-bankrupt" sector, while those firms having a Z-score below 1.81 are all bankrupt; the area between 1.81 and 2.99 will be defined as the "zone of ignorance" or "grey area" because of the susceptibility to classification error (Altman, 1968: 606).

In his Z_2 model, Altman (1983) estimated the Z-score for private firms; where in T4 (market value of equity / book values of total liabilities), he substituted the market value of equity with the book value of equity. As a result of this re-estimation of variables, the coefficients changed from

$$Z = 0.012T1 + 0.014T2 + 0.033T3 + 0.006T4 + 0.999T5 \text{ to}$$

$$Z_2 = 0.717T1 + 0.847T2 + 3.107T3 + 0.420T4 + 0.998T5$$

2.8. The relevance of Altman models in modern day prediction of company failures

Company failure and failure prediction has become a much talked about and researched topic in corporate finance in recent years. The reasons for the renewed interest is as a result of “the negative spiral in the general economic environment, the increased availability of data and statistical techniques, the extended academic research on the impact of market imperfections and information asymmetry and the introduction of the New Basel Capital” (Balcaen & Ooghe, 2004:1).

Balcaen and Ooghe (2004) have studied numerous models (earlier and latter ones), particularly comparing their classification results and / or prediction abilities. The results of these studies seem to indicate that “we may question the benefits to be gained from using the more sophisticated alternative methods” (Balcaen & Ooghe, 2004: 29).

Exhibit 9: Overview of the most popular alternative models applied in corporate failure prediction

Method	Main advantages	Main drawbacks
Survival analysis	— account for time dimension of failure — gives likely time to failure — no assumption of dichotomous dependent variable — easy interpretation	— not designed for classification — assumption: failing and non-failing firms belong to the same population — sample construction may affect hazard rates — requires homogenous lengths of failure processes in sample
Decision trees	— No strong statistical data requirements — allows for qualitative data — can handle noisy and incomplete data — user friendly: clear output	— specification of prior probabilities and misclassification costs — assumption: dichotomous dependent variable — relative importance of variables unknown — discrete scoring system cannot be 'applied'
Neural networks	— does not use pre-programmed knowledge base — suited to analyze complex patterns — no restrictive assumptions — allows for qualitative data — can handle noisy data — can overcome autocorrelation — user-friendly: clear output robust and flexible	— requires high quality data — variables must be carefully selected a priori — requires definition of architecture — possibility of illogical network behavior — large training sample required

Source: Modified from Balcaen and Ooghe (2004:22).

2.9. Alternative Popular Models: Survival analysis, Decision trees and Neural networks

The alternative models that have increasingly been used in failure prediction in recent years are Survival analysis, Decision trees and Neural networks. **Exhibit 9** above outlines and describes the advantages and disadvantages of these alternative popular models.

What stands out from the features described in the above table is that the survival analysis method accounts for time dimension of failure, allows for time-varying independent variables (making it easy to incorporate economic data into the model) and gives likely time to failure. The last point is perhaps the most important distinguishing feature of this model as it adds a prediction dimension to the time of failure. The disadvantage of this model is that its assumption is that failing and non-failing firms belong to the same population and are only separated over time by survival risk as a result of qualities inherent in the independent variables (ratios) and dependent variable (economic conditions).

The decision tree, whilst a relatively simple procedure has the disadvantage that the relative importance of the variables is unknown.

The neural network models are suited to analyze complex patterns, however run the risk of illogical network behavior.

From their review and analysis of these alternative models, Balcean and Ooghe conclude as follows; “a closer look at the features of the alternative modeling methods, reveals that they are computationally much more complex and advanced than the rather simple classical cross sectional statistical methods of MDA, logit, probit and linear probability models” (Balcaen & Ooghe (2004): 23).

Perhaps the most important observation from these authors’ work is in the conclusion that the differences in prediction accuracy appear at first sight not to be statistically significant and that the only difference in predictive performances found to be significant, is the difference between the logit model and survival analysis, one year prior to failure. And here, the logit method seems to be better than the survival analysis model (Balcaen & Ooghe, 2004: 25). Aziz and Humayon (2006: 29) also conclude in their findings that "the predictive accuracies of different models seem to be generally comparable, although artificial intelligent expert system (AIES) models perform marginally better than statistical and theoretical models".

It must be stressed that Balcaen and Ooghe (2004) analyzed a big number of studies, even beyond the three additional alternative models mentioned, with different research methodologies. To tease out accuracy and predictive performance of these models is rather a difficult task; and perhaps more studies along the lines of met-analysis need to be conducted in order to provide more definitive pronouncement on the performance of these models. What is important from this study though is that it does not conclude that the MDA or Altman models are inferior to the newer models.

2.10. Prediction Models with a financial statement analysis logic

Amongst the numerous other prediction models, the ones with financial statement analysis logic are of particular interest since they can be seen as an additional technique to financial analysis. **Exhibit 10** below provides a brief description of these models modified from an exhaustive table produced by Aziz and Humayon (2006: 19).

Exhibit10: Models with financial statement analysis logic

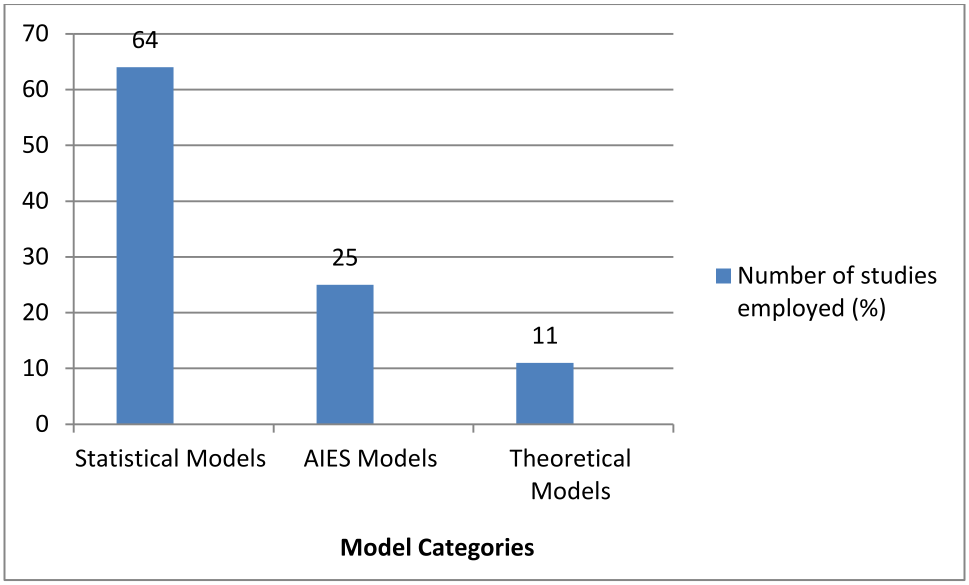
Model	Main features
Balance sheet decomposition measures (BSDM) / entropy theory	The bases for this model are that firms constantly try to maintain equilibrium in their financial structure. If a firm's financial statements reflect significant changes in the composition of assets and liabilities on its balance-sheet it is more likely that it is incapable of maintaining the equilibrium state. If these changes are likely to become uncontrollable in future, one can foresee financial distress in these firms.
Cash Management Theory	Short-term management of corporate cash balances is a major concern of every firm. An imbalance between cash inflows and outflows would mean failure of the cash management function of the firm, persistence of which may cause financial distress to the firm and, hence, bankruptcy.
Gambler's ruin theory	In this approach, the firm is constantly playing the probability of loss, continuing to operate until its net worth goes to zero (bankruptcy). With an assumed initial amount of cash, in any given period, there is a net positive probability that the firm's cash flows will be consistently negative over a run-off period, ultimately leading to bankruptcy.
Credit risk theories	Credit risk theories are linked to the Basel I and Basel II accords and mostly refer to financial firms. Credit risk is the risk that any borrower/counterparty will default, for whatever reason. Following the Basel II guidelines, a number of recent attempts have been made to develop internal assessment models of credit risk.

Source: Modified from Aziz and Humayon (2006: 19)

The ranking below **(Exhibit 11)** suggests that "the performance of MDA and Logit models (with lower adjusted standard deviations of 0.34 and 0.47, respectively) may be more reliable" (Aziz & Humayon 2006: 26).

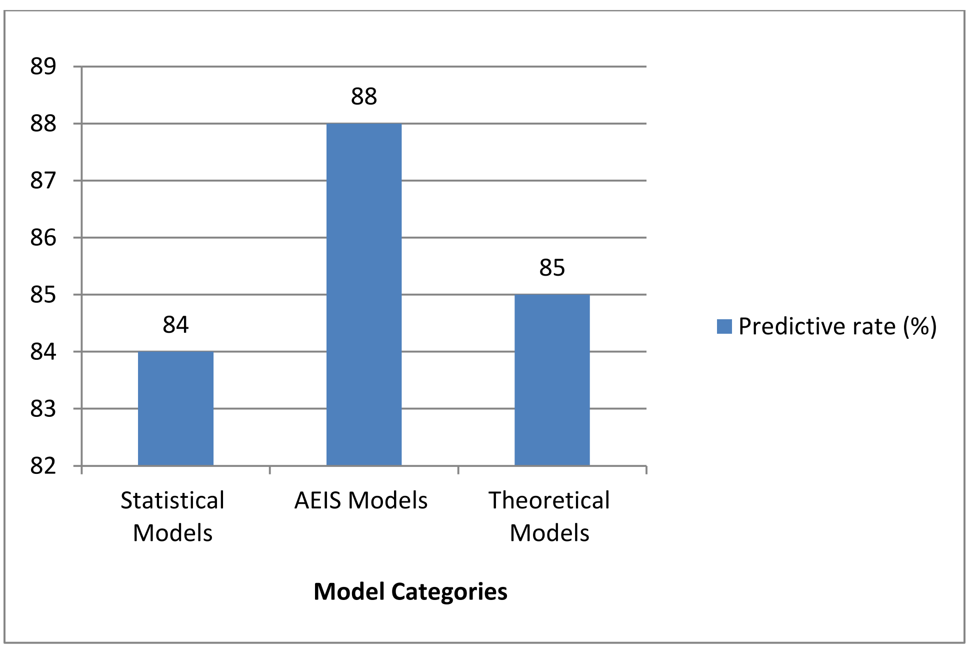
Among the individual models the MDA was the most employed at 30.2% of the total. The average overall predictive accuracy (OPA) of all the models is 85.2% of which that of MDA is 85%, ranking it very well amongst its competitor models, both in its category of statistical models and other categories such as artificially intelligent expert systems (AEIS) and Theoretical Models (**Exhibit 12** below).

Exhibit 11: Proportion of models categories employed by past studies



Source: Aziz & Humayon (2006: 26)

Exhibit 12: Overall predictive accuracy of different model categories



Source: Aziz and Humayon (2006: 27)

2.11. Theoretical debates around the earlier bankruptcy models

In her article, Evolution of the Bankruptcy Studies, Cybinski (2001), raises a few theoretical but valid arguments pointing to the potential weaknesses of the current bankruptcy models in general. She argues that "bankruptcy models have been concerned with prediction of bankruptcy before there is even a theoretical explanation of the phenomenon of bankruptcy" (Cybinski 2001: 29). Cybinski concedes that the early bankruptcy models, of which the Altman models are part, have had varying degree of successes in classifying companies into the bankrupt and non-bankrupt categories. The success of the earlier models is that researchers have been able to apply the techniques of MDA or logit analysis to the groups of healthy and distressed firms to produce classification instruments as well as predicting new cases from the derived formulae (Cybinski 2001: 29). The other shortcoming inherent in the logit and MDA analysis is that the dependent variable of failures "is not a dichotomy but rather a continuum" (Cybinski 2001: 30). Cybinski then makes the assertion that the model formulations, not surprisingly, are most successful, "when the data conforms to the expectation that the two groups are already separated on this continuum –i.e. bankrupt and non-risky surviving group" (Cybinski 2001: 31).

Mensah, in considering the importance of economic conditions in the timing of bankruptcy, asserts that the actual occurrence of bankruptcy is usually dependent on coupling of the correctly identified characteristics of failing companies with certain economic events (Mensah, 1984: 393). These observations suggest that if a firm is already vulnerable to failure, tight labour market conditions and low levels of expenditure in the economy at this time can have disastrous consequences on the ultimate solvency of the firm (Cybinski 2001: 37).

2.12. Generalizability of the Altman Z-score

Grice and Ingram (2001) question the generalizability of Altman's model and their argument is based on the fact that the model was used to study companies from the 1950s and 1960s. The questions they ask in their paper are: (i) is Altman's original model as useful for predicting bankruptcy in recent periods as it was for the period in which it was developed and tested, (ii) is the model as useful in predicting bankruptcy of non-manufacturing firms as it is for predicting that of manufacturing firms, (iii) is the model as useful in predicting financial distress conditions as it is useful in predicting bankruptcy (Grice & Ingram, 2001: 53).

Grice and Ingram's results suggest that better accuracy can be achieved by re-estimating the coefficients using samples from periods close to the test periods (Grice & Ingram, 2001: 60). This statement is not necessarily in contradiction to the Altman model since the Altman models lend themselves to improvement by using updated coefficients. Altman himself is open to the idea of reshuffling the coefficients in accordance with the situation and type of industry under study. Altman has continuously been improving his models to such an extent that his latest model called the Zeta-score is slightly different from the Z-score both in the way the coefficients have changed as well as the fact that additional ratios have been used. Grice and Ingram's concerns are based on studies performed by various authors indicating that coefficients of the independent variables change over different economic periods. Begley et al (1996: 268) also showed that "although models perform relatively well during the period in which they were estimated, they do not perform well in more recent times even when the coefficients were re-estimated". Grice and Ingram's (2001: 54) deduction therefore is that "it is unlikely that Altman's model performed equally well in all financial periods". This is understandable as inflation increases the cost structure whilst interest rates will increase the cost of debt as well as credit availability in turn.

The second concern of Grice et al (2001) is whether the models hold in companies other than manufacturing. Platt and Platt (1991: 1193) showed that bankruptcy models that included industry-relative ratios produced improved prediction accuracy compared to models that only included unadjusted ratios. The Platt and Platt (1991) study doesn't shed new light on the topic as this point had been factored in by Altman when he proposes that coefficients need to be re-estimated for different industries.

The third concern of Grice et al is whether the Altman model can predict financial distress as well as it predicts bankruptcy. The Altman model does grade the possibility of bankruptcy as unlikely, indifferent and most likely. This in itself can be seen as degrees of financial distress. Since this a quantitative model, one cannot expect any further qualitative descriptions of types and causes of financial distress. It suffices to say that the lower the Z-score the more the financial distress and therefore the higher the risk of bankruptcy. Altman also observed that "all of the discriminant coefficients displayed positive values", suggesting that the greater the firms distress potential, the lower the discriminant score (Altman, 2000: 15).

The essence of the results of the Grice and Ingram study is that "because ratio coefficients are not stable over time, over different industries as well as amongst representative proportionate samples of bankrupt and non-bankrupt firms, to improve the accuracy of the Z-scores in these settings, ratios need to be re-estimated for the different settings" (Grice el al 2001: 60). This is not in contradiction to Altman's view-point but rather serves to emphasize the need for re-estimating ratio coefficients and improving the model, as Altman himself has been doing.

Ooghe and Balcaen (2007: 33) studied the generalizability of the following models on a Belgian dataset; Gloubos-Grammatikos, Keasey-McGuinness, Ooghe-Joos-De Vos, Zavgren, Altman and Bilderbeek models. The Altman and Bilderbeek models showed very poor results in this study (Ooghe & Balcaen, 2007). The methodology of this study was to include only models estimated with linear discriminant analysis and logistic regression. However the Altman model (1968) which is an MDA model is also validated in this dataset. This could be the reason why Altman's model performed poorly.

Diakomihalis (2012) studied the bankruptcy predictions for different hotel categories in Greece, aiming to determine the zone of discrimination classified as a certainty for bankruptcy. The hotel industry on one level is similar to the healthcare industry in that it is a service industry where there are no commodities sold and therefore no high figures of cost of goods sold or inventory management. On the other hand hotels could hold very high total assets if the buildings are owned by the entity. Diakomihalis (2012: 109) illustrated that the Altman model holds well in service industries, with the Z_1 and Z_2 models attaining a very close accuracy level of 88.24 and 83.33 respectively.

Court and Radloff (1993: 19) proposed a two stage prediction failure model that takes into account the macroeconomic realities of the time the firm is being assessed. The model proposed is a significant departure from the traditional method of failure prediction whereby a single failure prediction score was obtained using only micro-economic variables. This model makes perfect sense from an academic perspective, however it is questionable whether this will find widespread business application as this model is complex to grasp and apply.

In addition to failure prediction, the Altman model can and has been applied to improve investment decisions. There has been close correlation between the Z-scores and the market values of stocks (Altman, 1968: 608).

It suffices to conclude this section by noting that Altman states that “while a subset of variables is effective in the initial sample, there is no guarantee that it will be effective for the population in general” (Altman, 2000: 16).

2.13. General limitations of prediction failure models

Corporate bankruptcy prediction is inherently vulnerable to problems arising from small samples as most firms with publicly available data do not go bankrupt (Aziz and Humayon 2006: 23). Small sample size may lead to Type I and Type II errors in hypothesis testing. Another source of Type I and Type II errors in prediction studies is the fact that the final estimate (such as the Z-score) is a continuum and not dichotomous. The zones of discrimination that depend on the Z_1 score are:

$Z_1 > 2.99$ = Safe Zone

$1.8 < Z_1 < 2.99$ = Grey Zone

$Z_1 < 1.80$ = Distress Zone

Classifying bankruptcy into safe zone, grey zone and distressed zone lends itself to misclassification, leading to Type I and Type II errors. Researchers conducting studies of any nature in most cases hypothesize that “a relationship between the investigated variables exists” (Cashen & Geiger, (2004: 154). Cashen and Geiger (2004: 154) further clarify that “statistical inference tests posit a null hypothesis (Ho: the phenomenon under investigation is absent, or there is no, or at best a trivial difference between the parameters being tested), which researchers contrast against the alternative hypothesis (Ha: the phenomenon is present, or there is a difference in the parameters being tested)”. Because the null hypothesis is typically rejected, the probability that such a decision would be erroneous (Type I error) has to be assessed in the form of α (alpha). There is also the probability (β) of failing to reject the null hypothesis when it is actually false. Such an error is commonly referred to as a Type II error and is usually less serious than the Type I error.

2.14. Summary of themes: main arguments and rebuttals

The arguments and rebuttals in the literature searched have been summarized and classified into the themes outlined in **Exhibition 13** below. It seems that Altman anticipated the kind of criticism against his models and hence preempted universal arguments that rebut most of the criticism against his models.

All the different bankruptcy prediction models have their pros and cons. Altman came under some criticism but his rebuttals make it a sufficiently robust model to use. The strength of the Altman model is that it can be applied over different economic periods in different types of industries and the model classifies financial distress into different categories.

Exhibit 13: Main themes, arguments and rebuttals

Themes	Main arguments
Causes of business failure Holt (2013)	Generic failure agents (GFA) are shown to be; managerial, financial, company characteristics, and macroeconomic conditions (in order of frequency): of which the first three reciprocally interact within conditions defined by the latter. Each GFA has a number of sub-causal agents (SCA) associated with it.
Statistical basis of predictive models Altman (2000)	Univariate modeling is prone to faulty interpretation and is potentially confusing Multivariate introduces the contentious questions of 'which ratios are most important in detecting bankruptcy, what weight should be attached to these ratios'.
Altman Z- score Altman (1968)	Z= 0.012T1 + 0.014T2 + 0.033T3 + 0.006T4 + 0.999T5 Where; T1 = working capital / total assets , T2 = retain earnings / total assets, T3 = earnings before interest and taxes / total assets , T4 = market value of equity / book values of total liabilities , T5 = sales / total assets Z = overall index Z-score zones: (Z_1 > 2.99 = Safe Zone), (1.8 < Z_1 < 2.99 = Grey Zone) and (Z_1 < 1.80 = Distress Zone)
Z_2 Model for Private firms Altman (1983)	Coefficients changed from: Z_1 = 0.012T1 + 0.014T2 + 0.033T3+ 0.006T4 + 0.999T5 to Z_2 = 0.717T1 + 0.847T2 + 3.107T3 + 0.420T4 + 0.998T5
The relevance of Altman in modern day prediction of failure analysis Balcaen and Ooghe (2004)	"We may question the benefits to be gained from using the more sophisticated alternative methods" Alternative & popular models: 1) Survival analysis (gives likely time to failure) , ii) Decision trees and Neural networks are computationally much more complex, iii) The predictive accuracies of different models seem to be generally comparable, although and iv) artificially intelligent expert system models perform marginally better than statistical and theoretical models
Predictive accuracy of various models Aziz and Humayon (2006)	Statistical models = 84%, AEIS models = 88% and Theoretical models = 85%
Theoretical debates on earlier bankruptcy models Cybinski (2001) (Mensah (1984)	"Models are predictive with no theoretical explanation of the phenomenon of bankruptcy "Dependent variable of failure is "not a dichotomy but rather a continuum" Vulnerable firms are pushed into failure by economic conditions (tight labour conditions and low levels of expenditure)
Generalizability of Altman's model Grice and Ingram (2001) Mensah (1984) Begley et al (1996)	Are Altman models generalizable over: – Different economic periods; coefficients change of different economic periods, interest rates and credit availability – Different types of industry – Can they identify and classify financial distress
In defense of Altman Altman (1968)	Procedure in building model: (i) observation of the statistical significance of variables (coefficients), (ii) evaluation of inter-correlations amongst the relevant variables (iii) observation of the predictive accuracy of the relevant variables & (iv) judgment of the analyst.
Limitations of prediction failure models Aziz & Humayon (2006)	Small samples may lead to misclassification (Type I and Type II errors) (Z_1 > 2.99 = Safe Zone), (1.8 < Z_1 < 2.99 = Grey Zone) and (Z_1 < 1.80 = Distress Zone)

Own creation (2013)

3. Research Methodology

The data was gathered from the website of the Council for Medical Schemes (CMS) of South Africa. The CMS is a statutory body that's primary objectives are to protect the rights and entitlement of members as well as ensuring that schemes, at all times, keep an adequate level of reserves to be able to meet their claims paying obligation in the unlikely but plausible event of a catastrophe that results in a significant number of members seeking and receiving medical care around the same time. The CMS collects and reports on comprehensive financial information on medical schemes annually. This information is made publicly available on the CMS website (www.medicalschemes.com).

3.1. Data selection and preparation

The data set was inclusive of both open and restrictive schemes. In the period 2002 to 2011 the data set consists of 153 schemes. Failed schemes are defined as those schemes whose reference numbers had dropped off the register of the CMS by the end of the period under study. As a result of the definition used for failed schemes, no restrictions were applied to include or exclude schemes into the study. The financial statements analyzed were from 2002 to 2011 (same fiscal period) for both failed and non-failed schemes. The financial statements of the schemes were adjusted for differences in reporting style prior to and after 2004, as most medical schemes introduced saving accounts from 2005. The naming convention in medical scheme financial statements is slightly different to that in general accounting. **Exhibit 14** below illustrates the accounting naming convention of medical schemes compared to that in general accounting.

Exhibit 14: Accounting naming convention for medical schemes

General Accounting naming convention	Medical schemes naming convention
Sales	Gross contributions
EBIT (Earnings before interest and Tax)	Net healthcare results
Net earnings / (loss)	Net surplus /(deficit) after consolidation results
Net working capital	Net working capital
Book value of equity	Net assets
Total liabilities	Total liabilities
Total assets	Total Assets

Source: Own Creation, 2013

The financial information collected were parameters constituting the ratios similar to that in the Altman Z_2 model. Information collected from the income statements was net contribution, net healthcare result, net surplus (deficit). The financial information collected from the balance sheet was trade and other receivables, trade and other payables, cash and cash equivalents, outstanding claims provisions, savings liability, total assets, net assets and solvency ratios.

3.2. Special considerations and assumptions in data selection

(i) The Altman Z_2 was used since medical schemes are not listed entities and therefore would not have market capitalization, hence the net assets were used instead of market capitalization.

(ii) Schemes generally do not carry much debt as a result most schemes did not have much long term debt on their balance sheets; outstanding claims provision and savings liability were included as scheme's long term debt – the reason for considering the above as long term debt and not short term debt was because these items were not included in the short term debt of schemes as reported by the CMS.

(iii) The definition of failed schemes is all schemes whose reference numbers fell off the data base in the period 2002 to 2011 – this assumption was made as it would have been impossible to accurately determine which schemes had indeed failed as there was so many mergers in the period and there was no legal declaration of bankruptcy amongst schemes as in the Altman study. This assumption has potential implications as it is likely to decrease the classification accuracy as well as increase the Type I and Type II error rates.

(iv) A decision was made not to eliminate outliers as this would have further reduced the already small sample size – this has a potential of skewing the data.

Gross contributions were preferred over Net contributions the rationale being that the savings liability was going to be added to total debt hence the entire contributions had to be considered.

3.3. Sample selection and time period

A times series case study approach was used in order to document the financial ratios and the Altman Z_2 score of all medical scheme (failed and non-failed) over a ten year period; from 2002 to 2011. This period was chosen to allow for a significant period of time in order to increase the chances of observing a significant number of scheme failures. New schemes were added and removed from the data base as schemes were registered and deregistered along the ten year period.

The term "failed" is preferred over bankrupt schemes since bankruptcy was not established. The definition of failed schemes is any scheme that ceased to exist irrespective of the cause for such cessation.

3.4. Variable Selection and adjustments

The variables selected were those applied by Altman in his work estimating the Z-score (Z_2) for private firms (Altman, 1983). The ratios selected are as follows:

T1 = (current assets – current liabilities) / total assets

T2 = Net surplus (deficit)/ total assets

T3 = Net healthcare results / total assets

T4 = Net assets / book values of total liabilities

T5 = Gross contributions / total assets

The coefficients applied were kept the same as worked out by Altman in his original Z_2 model and were only changed when the medical scheme Z-scores were calculated:

The Z equation used was the original Altman Z score equation as below:

$Z_2 = 0.717T1 + 0.847T2 + 3.107T3 + 0.420T4 + 0.998T5$

The zones of discrimination depending on the Z_2 score are:

$Z_2 > 2.9$ = Safe Zone

$1.23 < Z_2 < 2.9$ = Grey Zone

$Z_2 < 1.23$ = Distress Zone.

3.5. Practical steps in the methodology

The methodology applied is a modification of the work by Moghadam et al (2003) which outlined similar steps as below:

(i) Failed schemes were identified by documenting serial financial data of all schemes in the period 2002 to 2011. The discontinuation or appearance of a scheme's reference number and data on the database would alert that a scheme had been discontinued or registered respectively. The discontinuation or registration was confirmed by the explanatory notes and comments on discontinued and registered schemes in the CMS report.

(ii) Discontinued schemes (both open and restricted) were classified as failed schemes whilst continuing schemes were classified as non-failed schemes.

(iii) The required financial data was extracted to calculate the ratios (T1 to T5) of the schemes.

(iv) The required financial ratios of the schemes were calculated.

(v) The means of the financial ratios were determined as well as the statistical significance between those of failed and non-failed schemes.

(vi) The Altman model in the SA medical schemes was validated by the following means:

- a) Comparison of variables (T1 to T5) and Z-scores of failed and non-failed schemes using the Mann-Whitney test
- b) Correlation matrices of the independent variables in relation to the Z-score
- c) Classification and error rates of the Altman prediction model in SA medical schemes (the predictions were based on data one and two years prior to failure).

(vii) New Z-score were established by re-estimation of new coefficients: the MDA was rerun using original variables (T1 to T5). The new Z-score was established through the following steps (Altman, 1968):

- a) Of the schemes already existing in 2002, the schemes that had failed in the period 2002 to 2011 were selected; of those selected schemes the data of 1 year prior to their failure was analyzed. Firms that did not have data 1 year prior to failure were excluded (for instance a firm failing in its first year of operation was excluded).

- b) Of the schemes already existing in 2002, the schemes that had not failed in the period 2002 to 2011 were selected (those that were still in existence at the end of the period).
- c) Thus a basic sample of 42 failed firms and 92 non-failed firms was arrived at, prior to any matching. Failed firms had total assets ranging from R1 487 000.00 to R781 355 000.00. All non-failed firms falling outside this range were excluded, resulting in a final sample of 42 failed firms and 81 non-failed firms. This exercise was to try and match schemes by asset size (similar to what Altman did in his study).
- d) An MDA was then performed using exactly the same variables (ratios) as previously used (T1 to T5).

(viii) An alternative Z-score was established: The MDA model was rub again using new variables.

The new variables were selected from what was thought to be significant drivers of sustainability of medical schemes. The following variables were selected:

- (current assets – current liabilities)/ Gross contributions
- Total assets / Gross contributions
- Net assets / Gross contributions
- Net healthcare results / Gross contributions
- Solvency ratios

The gross contribution was chosen as it is a significant denominator in most ratios in accounting. The solvency ratio also has the gross contribution as a denominator.

3.5.1. Calculation of accuracy (classification and error rates)

It is important to contextualize the methodology employed in the accuracy calculation. The purpose of the original Altman research (1968) was to devise a tool that could predict a company's fate in terms of the following categories: failed, non-failed and indeterminate. The question of accuracy calculation methodology was never dealt with in the study since Altman never had to validate his own model. However for other researchers seeking to validate the Altman model in different countries and circumstances, the methodology of calculating accuracy becomes essential.

It is statistically more appropriate to exclude the counts of the grey areas (the schemes which are indeterminate with regards to having failed or not failed). This calculation is appropriate in a 2 by 2 table context only, and not in the 2 by 3 table (which includes those companies falling into the grey zone). If the above formula is used in context of the 2 by 3 table, then the denominator in our accuracy and error classifications includes the schemes in the indeterminate grey zone, which are thus not represented in the numerator at all.

This study will show classification and error rates in which grey zones counts were both included and excluded.

3.5.2. Methodology used for reestablishing alternative Z-scores was as follows

A stepwise model building procedure was followed in order to obtain the "best" model. Both forward (add-on) and backward (deduction) models were run with the following specifications:

Forward build: Tolerance of 0.03, F to enter of 0.5, F to removal of 0.0.

Backwards build: Tolerance of 0.03, F to enter of 1.0, F to removal of 0.5.

Model resulting from Forwards build: T1, <u>**T2**,</u> T4, T5, b, c, d

Model resulting from Backwards build: T1, T4, T5, b, c, d

The Backwards build model was selected given that **T2** represents operating surplus (deficit) and that **d** (Net healthcare results / Gross contributions) was already in the model.

4. Results

The results of the study will be reported on in the following format:

(i) Descriptive statistics of the schemes in the CMS database

(ii) Validation of the Altman Z_2 model amongst the medical schemes in South Africa in terms of accurately classifying Z_2 scores of ≤ 1.23 and ≥ 2.9 into the a priori groups of failed and non-failed schemes respectively.

(iii) Establishing new Z-scores (and limits) by re-estimation of new coefficients: from rerunning the MDA model using original variables (T1 to T5).

(iv) Establishing alternative Z-scores (and limits): by rerunning the MDA model using new variables.

4.1. Basic descriptive statistics

Exhibit 15 below depicts the numbers and percentages of failed schemes in the data set in the period 2002 to 2011.

Exhibit 15: Number and frequency of failed schemes (both open and closed) in the period 2002 to 2011.

Year of Failure	Freq.	Percent	Cum. Freq
2002/2003	8	14.55	14.55
2003/2004	4	7.27	21.82
2004/2005	5	9.09	30.91
2005/2006	5	9.09	40
2006/2007	4	7.27	47.27
2007/2008	7	12.73	60
2008/2009	8	14.55	74.55
2009/2010	7	12.73	87.27
2010/2011	7	12.73	100
Total	55	100	

There has been no less than at least 7% failure rate per year amongst schemes in this period (2002 to 2011)

Exhibit 16 below depicts the percentage of schemes that failed over the period 2002/2003 to 2011/2012 amongst open and restricted schemes. There was a higher percentage failure rate amongst the open schemes. This phenomenon can be explained by the fact that open schemes are more vulnerable as they attract older and sicker members compared to restricted schemes that draw their members from a younger population that is still in the employ of companies.

Exhibit 16: Percentage of overall failed schemes over the period 2002/2003 to 2011/2012

Failure	Type		Total
	Open	Restricted	
No	27	71	98
Yes	25	30	55
Total	52	101	153
% Failed	48.1%	29.7%	35.9%

Annexure A depicts a list of all failed schemes (open and restricted), in order of the year in which the schemes were registered.

4.2. Validation of the Altman Z-score in the SA medical scheme Industry

There are various observational methods one can use to validate the Altman model in a particular setting or industry. The following observations were used in this study; (i) the Mann-Whitney test was used in the comparison of variables (T1 to T5) and Z_2-scores of failed and non-failed schemes, (ii) The Spearman's Rho regression analysis was used to determine the correlation of the variables (T1 to T5) with the Altman Z_2-score for the failed and non-failed schemes (open and restricted) (iii) the classification and error rates of the Altman model in SA medical schemes was determined.

4.3. Comparing variables and Z-scores of failed and non-failed schemes

Even within the context of the MDA model, the correlation and coefficients of ratios still convey a lot of information about the reason for the differences between the failed and non-failed organizations. **Exhibit 17** below illustrates a summary of the statistical differences (Mann-Whitney test) between ratios of failed and non-failed schemes in the period 2002/2003 to 2011/2012. Note the statistical differences are between ratios T2, T3, T4 and the Z-score: not only are there statistically different values in the Z-score, but also in the ratios T2 (retained earnings / total assets), T3 (earnings before interest and taxes / total assets) and T4 (market value of equity / book values of total liabilities).

Exhibit 17: Comparing medians of variables (T1 to T5) and Z-scores for failed and non-failed (all schemes) using the Mann-Whitney test (period 2002/2003 to 2011/2012)

Mann-Whitney Tests: comparison of T1 through 5 and Z					
Variable	Failed Schemes	Non-Failed Schemes (Median)	z-score (test statistic)	p	Conclusion
	Median (IQR)	Median			
T1	0 (-0.03 - 0.04)	-0.01 (-0.04 - 0.01)	-1.515	0.1297	NS
T2	0 (-0.09 - 0.12)	0.06 (0.02 - 0.12)	2.572	0.0101	S
T3	-0.05 (-0.15 - 0.03)	0 (-0.05 - 0.07)	2.689	0.0072	S
T4	2.09 (0.82 - 4.58)	5.78 (3.21 - 14.04)	3.976	0.0001	S
T5	1.2 (0.75 - 3.03)	2.3 (0.87 - 6.17)	1.777	0.0756	NS
Altman Z	2.69 (1.48 - 4.80)	6.87 (3.66 - 11.93)	4.401	<0.0001	S

Exhibit 18 below show that there were statistical differences between the ratios T2, T3, T4 and the Z-score of failed and non-failed open schemes, similar to that of the total schemes. On the other hand there were statistical differences between the ratios T1, T4, T5 and the Z-score of failed and non-failed restricted schemes, different to that of

the total schemes.

Exhibit 18: Statistical differences between ratios of failed and non-failed schemes separately in the period 2002/2003 to 2011/2012

Mann-Whitney Tests: comparison of T1 to T5 and Z						
Type	Variable	Failed Schemes	Non-Failed Schemes (Median)	z-score (test statistic)	p	Conclusion
		Median (IQR)	Median			
Open	T1	0 (-0.11 - 0.02)	-0.01 (-0.04 - 0.02)	0.352	0.7249	NS
	T2	-0.01 (-0.11 - 0.12)	0.05 (0.02 - 0.12)	2.138	0.0325	S
	T3	-0.09 (-0.18 - 0.07)	-0.01 (-0.03 - 0.06)	2.111	0.0348	S
	T4	1.5 (0.35 - 4.05)	3.83 (2.4 - 6.8)	2.752	0.0059	S
	T5	2.22 (1.31 - 4.15)	3.85 (1.25 - 5.56)	1.029	0.3037	NS
	Z	3.43 (0.79 - 4.92)	5.88 (3.71 - 8.52)	2.528	0.0115	S
Restricted	T1	0.02 (0 - 0.05)	-0.01 (-0.04 - 0.01)	-2.509	0.0121	S
	T2	0.02 (-0.04 - 0.15)	0.06 (0.01 - 0.12)	1.37	0.1708	NS
	T3	-0.03 (-0.12 - 0.01)	0.01 (-0.06 - 0.08)	1.643	0.1003	NS
	T4	2.37 (1.77 - 6.75)	7.62 (3.76 - 15.87)	2.4	0.0164	S
	T5	0 (-0.03 - 0.04)	1.97 (0.66 - 7.04)	2.145	0.0319	S
	Z	2.27 (1.48 - 4.62)	7.14 (3.66 - 12.36)	3.517	0.0004	S

Annexure B illustrates the descriptive statistics of failed and non-failed schemes of open and restricted schemes by year (calculated using the last year for each company - either 2011/2012 or the year of failure).

4.4. Correlation between the independent variables and the Z-scores

The correlation of the ratios to the Z-score essentially suggests what ratios are the major drivers of the Z-score. By knowing what ratios are the major drivers, one can then improve those ratios in order to effect a turn-around of the business. Only in the failed open schemes (**Exhibit 19** below) was there a statistical difference in correlation between the Z-scores and the variables T1, T2, T3 and T4. This pattern is similar to the ratios that displayed a statistically significant difference between failed and non-failed companies in the Altman study. In summary, there is always a correlation between T4 and the Z-score (asset turnover and survival), in all schemes except open non-failed, All the non-failed schemes showed a strong correlation between the T5 and the Z-score, suggesting that high equity, low debt or both was a significant factor in the survival of schemes. It is interesting to note that equity in the case of medical schemes is equivalent to reserves.

Exhibit 19: Correlation matrices of schemes in the category of open failed

Correlation matrix for Failed Open schemes						
	T1	**T2**	**T3**	**T4**	**T5**	**Z**
T1	1					
T2	0.1929	1				
	0.491					
T3	0.2571	0.9536	1			
	0.3549	<0.0001				
T4	0.2607	0.3464	0.1643	1		
	0.348	0.2059	0.5585			
T5	-0.0071	-0.2321	-0.1357	-0.5929	1	
	0.9798	0.4051	0.6296	0.0198		
Z	0.5929	0.5536	0.55	0.4964	0.075	1
	0.0198	0.0323	0.0337	0.0598	0.7905	

In general, there was a significant correlation between earnings and equity/ debt ratio (T2, T3 and T4) and the Z-score in all the schemes (overall, open and restricted), whilst there was a strong correlation between equity/debt ratio and asset turn over (T4 and T5) and the Z-score in all non-failed schemes (overall, open and restricted). Note, the fact that there is such a strong correlation between T1 and T2 serves as a reasonability check, as these two variables are expected to be well correlated as EBIT / Total assets and Net Earnings/ Total assets are closely related to each other.

4.5. Accuracy of the Altman prediction model amongst SA medical schemes

Annexure C shows the trend in accuracy and error rates of schemes classified into failed or non-failed category as well as percentages of schemes that could not be classified into neither category. Accuracy was assessed and calculated as follows: {(True Negatives + True Positives)/Total}. This calculation is appropriate in 2 by 2 table context only, and not in the 2 by 3 table (which includes those companies falling into the grey zone). If the above formula is used in the context of the 2 by 3 table, then the denominator in our accuracy and error classifications includes the schemes in the indeterminate grey zone, which are thus not represented in the numerator at all.

4.6.1. Accuracy and error rates calculations with grey area counts included

In this section accuracy was calculated with grey zone counts included. Type I and II error rates are provided, together with the overall classification accuracy rate and the overall classification error rate.

- Type I error is the ratio of failed schemes incorrectly classified to the total number of failed schemes.
- Type II error is the ratio of non-failed schemes incorrectly classified to the total number of non-failed schemes.
- Classification accuracy is the ratio of correctly classified schemes (failed and non-failed) to the total number of schemes.
- Classification error is the ratio of incorrectly classified schemes (failed

and non-failed) to the total number of schemes

Exhibit 20 below illustrates the predictive value of the model over the period 2003 to 2011; for all schemes one and two years prior to failure. The general trend is that the predictive value is 60% and above, with an average combined error rate (Type I and Type II errors) of around 10%; except in years 2003/2004 and 2004/2005 for one year and two years prior to failure (respectively) where the predictive values are both 48%.

Exhibit 20: Classification rate and error rate of the MDA model for *__all schemes__* (over the period 2003 to 2012)

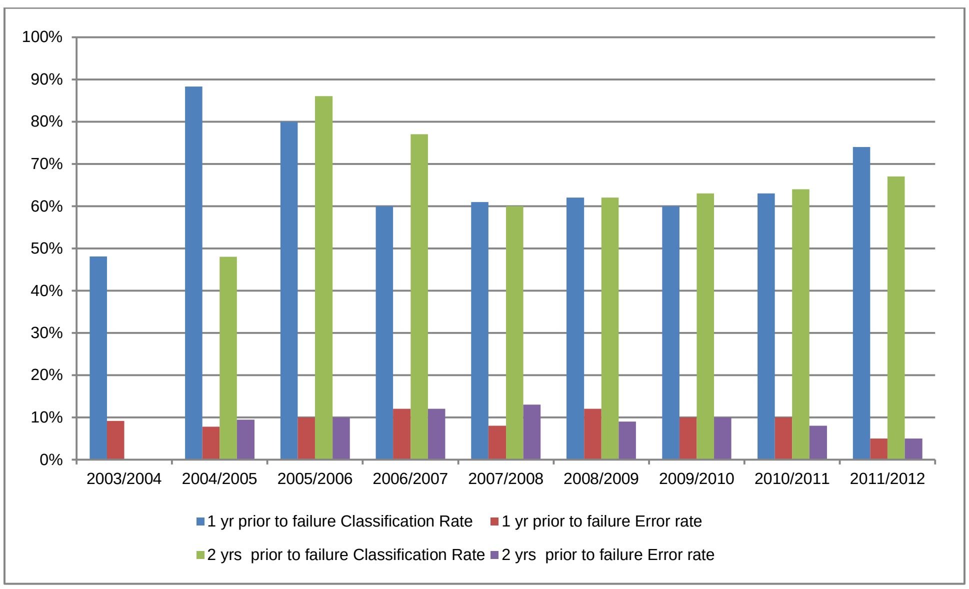


Exhibit 21 and 22 below illustrate the predictive values of open and restricted schemes respectively with restricted schemes performing better than open schemes in both predictive values and error rates.

Exhibit 21: Classification rate and error rate of the MDA model for *open schemes* (over the period 2002 to 2011)

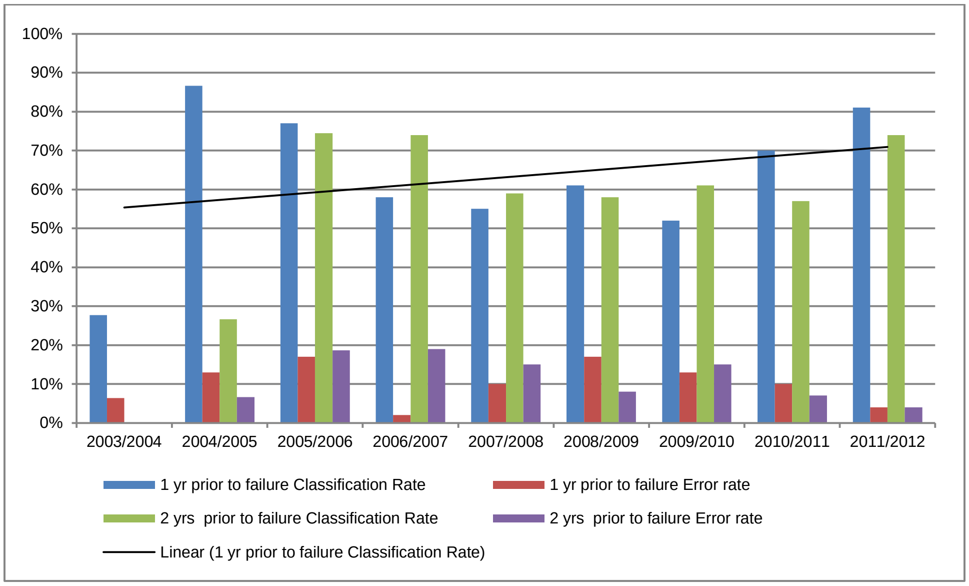
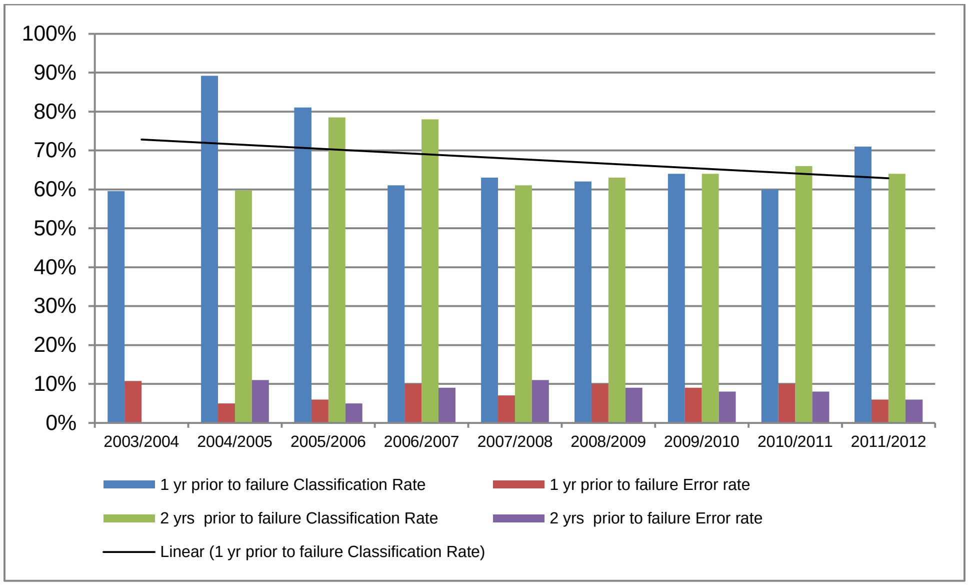


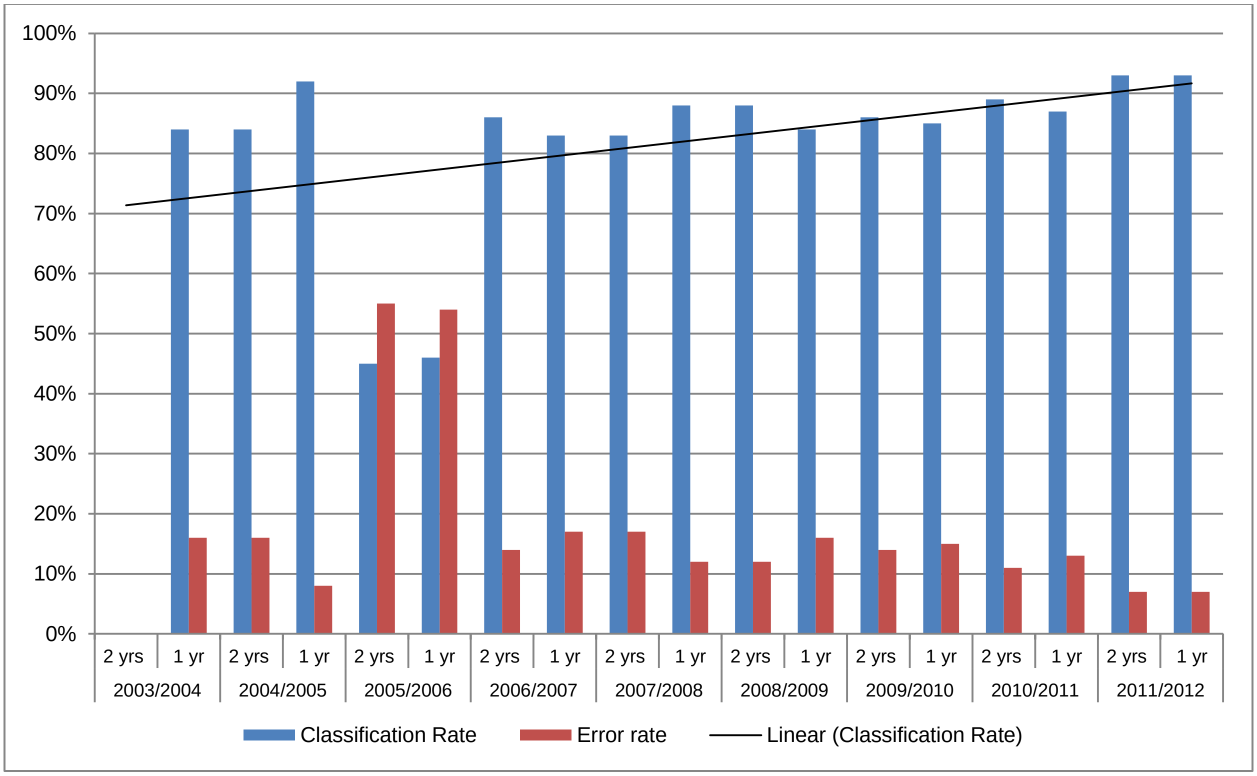
Exhibit 22: Classification rate and error rate of the MDA model for *restricted schemes* (over the period 2002 to 2011)



4.6.2. Accuracy and error rate classifications excluding the grey area counts

In this section the grey zone counts have been excluded in the accuracy calculation. This methodology is favored for the reasons explained above (section 3.5.1. p51). **Exhibit 23** below illustrates the accuracy and error rates when the grey zone counts have been excluded.

Exhibit 23: Classification rate and error rate of the MDA model for *__all schemes__* (over the period 2002 to 2011)



The accuracy rates are much more superior when the grey zone counts have been excluded. The average classification rates in the period 2003 to 2011 are as follows: 82% accuracy rate and 17.9% error rate. An anomaly was observed in the year 2005/2006 where the accuracy and error rates are 45% and 55% respectively and 46% and 54% respectively for two years and one year prior to failure respectively. The linear trend line inserted in the above graph shows that the accuracy improves from 72% to 91% between the period 2003/2004 to 2011/2012. Open scheme performed as follows: 84%, 16% and 25% for accuracy rate, error rate and percentage indeterminate respectively. Restricted schemes performed better that open schemes: 89%, 11% and 24% for accuracy rate, error rate and percentage indeterminate respectively.

4.7. Re-estimated coefficients: rerunning the MDA using original variables

This process leads to the generation of the new Z-scores for failed schemes, non-failed schemes, as well as their grey zones. These Z-scores will henceforth be named Medical Scheme Z-scores (MS_Z-scores). This process is similar to the original analysis Altman used to arrive at his original Z-scores. The purpose of this exercise is to see if the re-estimation of the coefficients will result in an improved classification and error rates, as suggested by Altman.

4.8. Classification tables of the new medical scheme Z-score (MS_Z-score)

Exhibit 24 below depicts the classification table of failed and non-failed schemes under the new MS_Z-score.

Exhibit 24: Re-substitution classification table of the MS_Z-score

True result	Classification		Total
	Non-Fail	Fail	
Non-Fail	61	18	79
%	77.22	22.78	100
Fail	20	20	40
%	50	50	100
Total	81	38	119
%	68.07	31.93	100

The above classification table is labeled as a re-substitution classification table because the same observations used in estimating the discriminant model were classified using this model. Note, there is much better classification accuracy in classifying non-failed schemes than in classifying failed schemes (81% vs. 38% respectively).

The re-substitution classification table often provides an overly optimistic assessment of how well the linear discriminant function will predict the failure status for observations that were not part of the training sample. A leave-one-out (LOO) classification table (**Exhibit 25** below**)** provides a more realistic assessment for future prediction. The LOO classification is produced by holding each observation out, one at a time building an LDA model from the remaining training observations, and then classifying the held out observation using this model.

Exhibit 25: LOO re-substitution classification table of the MS_Z-score

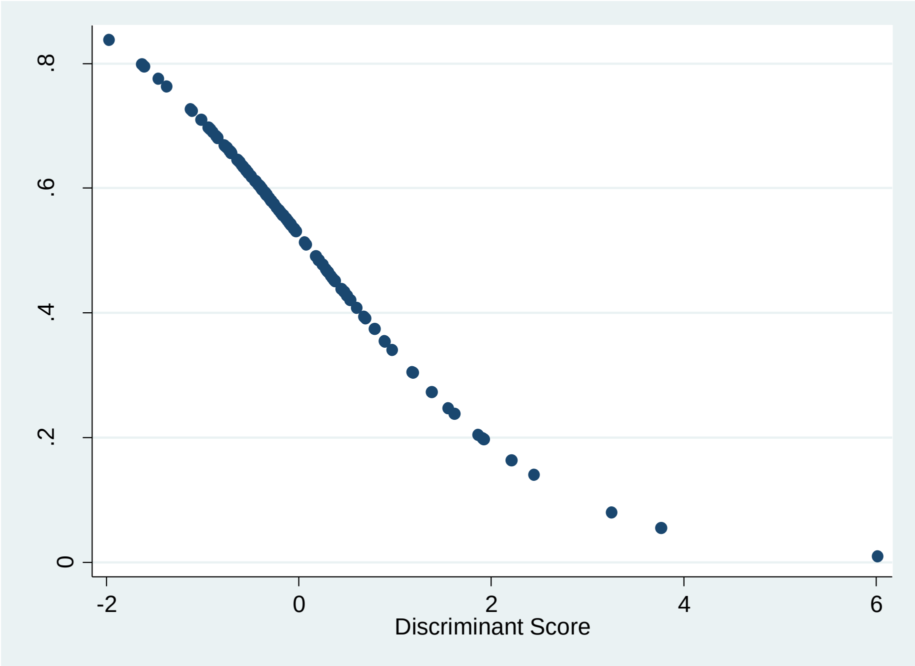
True result	**LOO Classification**		**Total**
	Non-Fail	Fail	
Non-Failed	61	18	79
%	77.22	22.78	100
Failed	21	19	40
%	52.50	47.50	100
Total	81	38	119
%	68.07	31.93	100

The LOO re-substitution classification model confirms that there is much better classification accuracy in classifying non-failed schemes than in classifying failed schemes (81% vs. 38% respectively as well).

Annexure D shows the re-substitution and leave-one-out classifications and posterior probabilities for those observations that were misclassified by the LDA model.

Exhibit 26 below illustrates the probability of being in the failed group (group 1) against the value of the discriminant score. This graph can again be regarded as another reasonability check since the curve of the graph is sigmoid as expected**.**

Exhibit 26: Plotting probability of being in the failed group (group 1) against the value of the discriminant score.



4.9. The new equation resulting from the re-estimation of coefficients

Below is the new MS_ Z-score equation that resulted from the re-estimation of coefficients:

Z= -1.77T1 -0.3123T2 -1.733T3 -0.031T4 +0.283T5

Note the negative values for T1 to T4.

4.9.1 Medians of the MS_Z values of the failed and non-failed schemes

Exhibit 27 below compares the medians of the MS_Z values following re-estimation of coefficients. There is a statistically significant difference (p=0.0004) between the medians of the MS_Z values of failed and non-failed schemes.

Exhibit 27: Comparing new MS_Z values of following re-estimation of coefficients

Fail status	Variable	N	Min	Max	Mean	Std Dev.	Median	25th Percentile	75th Percentile
Non-Failed	Z	79	-1.496	3.729	0.214	0.707	0.122	-0.143	0.429
Failed	Z	40	-1.129	6.491	0.995	1.414	0.639	0.117	1.662

Man-Whitney test: MS_Z= -3.533, p=0.0004

Exhibit 28 below examines individual variables following the process of re-estimation of coefficients. There are statistically significant differences between the medians of the variables T2 toT5 of failed and non-failed schemes (Mann-Whitney tests)**.** The p values for the difference between variables T2 to T5 are p= 0.002, p=0.0017, p=0.001 and p=0.0101 respectively. There is no statistically significant difference in the medians of the variable T1 (p=0.2515) (**Exhibit 29** below)

Exhibit 28: P value of the medians of the variable T1 to T5 following re-estimation of coefficients

Fail status	Variable	N	Min	Max	Mean	Std Dev.	Median	25th Percentile	75th Percentile
Non-Failed	T1	81	-0.45	0.37	-0.01	0.08	-0.02	-0.03	0.01
	T2	81	-0.81	0.49	0.04	0.15	0.06	0.01	0.11
	T3	81	-0.96	0.26	-0.05	0.18	-0.02	-0.09	0.03
	T4	79	0.76	56.44	9.88	9.93	5.40	3.11	15.16
	T5	81	0.21	4.31	1.46	0.96	1.16	0.76	1.73
Failed	T1	42	-0.60	0.43	-0.05	0.17	-0.05	-0.08	0.04
	T2	41	-2.18	0.46	-0.11	0.41	-0.01	-0.20	0.06
	T3	42	-2.46	0.41	-0.26	0.53	-0.12	-0.35	-0.03
	T4	41	-0.73	27.95	5.86	7.20	2.74	1.01	10.12
	T5	42	0.19	9.66	2.74	2.56	1.67	0.93	3.48

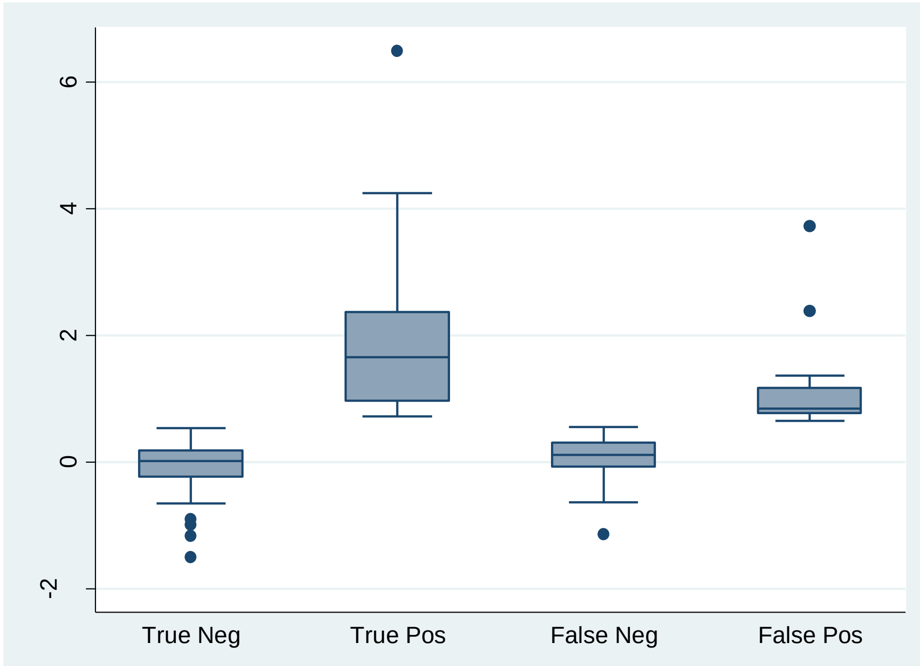
Exhibit 29: Mann-Whitney tests across variables of failed and non- failed schemes

Variable	Z	P
T1	1.147	0.2515
T2	3.092	0.002
T3	3.147	0.0017
T4	3.284	0.001
T5	-2.571	0.0101

4.9.2. Cut-off values for new MS_Z-score

The cut-off values for the new MS_Z-score are graphically represented in the **Exhibit 30** below. The limits are much lower than the revised Altman Z-score for private firms.

Exhibit30: Cut-off values for the new MS_Z-score



New MS_Z-score cut-off values:

> 1.17 = Non-failed schemes

0.02 to 1.17 = grey zone

< 0.02 = failed schemes

4.10. Alternative Z-values (Alt_MS-scores): rerunning MDA using new variables

This process leads to the generation of an alternative medical scheme Z-score (Alt_MS_Z-scores) for failed schemes, non-failed schemes, as well as those in the grey zone. These Z-scores will henceforth be named Alternative Medical Scheme Z-scores (Alt_MS_Z-scores). This process is similar to the original analysis Altman used to arrive at his original Z-scores. The purpose of this exercise is to see if the re-running of the MDA on new medical scheme variables will result in an improved classification and error rates, as suggested by Altman.

A stepwise model building procedure was followed in order to obtain the "best" model. Both forward (add-on) and backward (deduction) models were run with the following specifications:

Forward build: Tolerance of 0.03, F to enter of 0.5, F to removal of 0.0.

Backwards build: Tolerance of 0.03, F to enter of 1.0, F to removal of 0.5.

Model resulting from Forwards build: T1, **T2,** T4, T5, b, c, d

Model resulting from Backwards build: T1, T4, T5, b, c, d

The new five established variables are therefore: T1, T4, T5, b, c, and d

4.10.1. Accuracy of the Alt_MS_Z-scores in the failed and non-failed schemes

Exhibit 31 below depicts the classification table of failed and non-failed schemes under the Alt_MS_Z-scores.

Exhibit 31: Re-substitution classification table of the Alt_ MS_Z-score

True result	Classification		Total
	Non-Fail	Fail	
Non-Fail	67	12	79
%	84.81	15.19	100
Fail	17	24	41
%	41.46	58.54	100
Total	84	36	120
%	70	30	100

The above classification table is labeled as a re-substitution classification table because the same observations used in estimating the discriminant model were classified using this model. Note, there is much better classification accuracy in classifying non-failed schemes than in classifying failed schemes (84% vs. 36% respectively).

Exhibit 32 below is a leave-one-out (LOO) classification table that provides a more realistic assessment for future predictions.

Exhibit 32: LOO re-substitution classification table of the Alt_MS_Z-score

True result	LOO Classification		Total
	Non-Fail	Fail	
Non-Fail	64	15	79
%	81.01	18.99	100
Fail	18	23	41
%	43.9	56.1	100
Total	82	38	120
%	68.33	31.67	100

The LOO re-substitution classification model confirms that there is much better classification accuracy in classifying non-failed schemes than classifying failed schemes (82% vs. 38%) respectively as well.

Exhibit 33 below shows good predictive values of failed schemes of select years and type of schemes. The rest of the other years had disappointing predictive values which are not worth considering. This observation is consistent with the earlier observation that there was generally better predictive value in the years prior to the introduction of savings (2005).

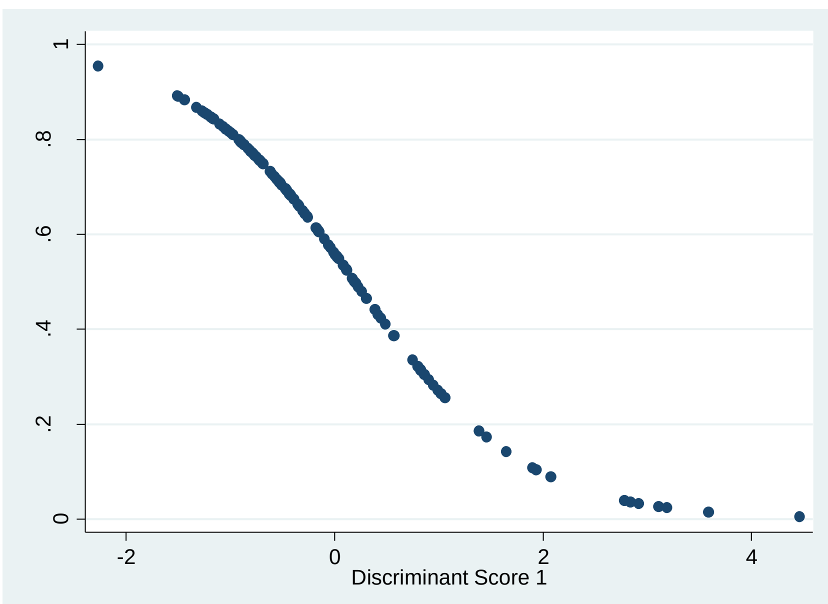
Exhibit 33: Years and type of schemes with good classification and error rates (Alt_MS_Z model)

Year	Year (Pred)	Outcome	Overall Classification rate	Overall Error rate
2003/2004	1 yr. prior to failure	Open	85%	15%
2003/2004	1 yr. prior to failure	Restricted	80%	11%
2004/2005	2 yrs. prior to failure	Open	87%	13%
2004/2005	2 yrs. prior to failure	Restricted	81%	11%

Annexure E shows the re-substitution and leave-one-out classifications and posterior probabilities for those observations that were misclassified by the LDA model whilst re-establishing the Alt_MS_Z-score.

Exhibit 34 below illustrates the probability of being in the failed group (group 1) against the value of the discriminant score. This graph can again be regarded as another reasonability check since the curve of the graph is sigmoid as expected

Exhibit 34: Plotting probability of being in the failed group (group 1) against the value of the discriminant value of the Alt_MS_Z-score.



4.10.2. The Alternative equation resulting from new variables

Below is the Alt_MS_ Z-score equation that resulted from the alternative variables and re-estimation coefficients:

$Z= -1.03T1 + 0.034T4 + 0.504T5 - 4.467c - 2.70d + 3.93b$

Note the negative values for T1, c and d.

Exhibit 35 below compares the medians of the Alt_MS_Z values following the introduction of new variables. There is a statistically significant difference (p=0.0004) between the Alt_MS_Z values of failed and non-failed schemes.

Exhibit 35: Comparing Alt_MS_Z values of failed and non-failed schemes

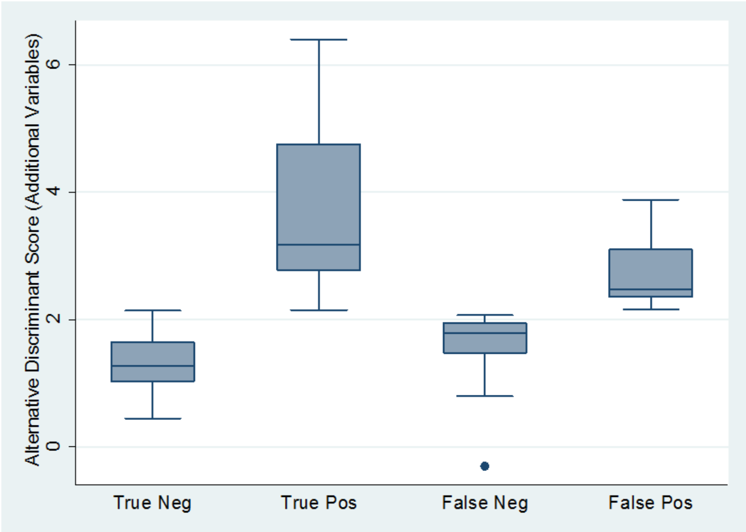
Fail status	Variable	N	Mini	Max	Mean	Std Dev.	Median	25th Percentile	75th Percentile
Non-Fail	Z	79	0.44	3.89	1.53	0.69	1.42	1.06	1.91
Fail	Z	41	-0.31	6.41	2.77	1.42	2.52	1.89	3.41

Man-Whitney test: Alt_MS_Z = -5.492, p<0.0001

4.10.3. Cut-off values for Alt_MS_Z-score

The cut-off values for the new Alt_MS_Z-score are graphically represented in **Exhibit 36** below. The limits are very close to that of the revised Altman Z-score for private firms.

Exhibit 36: Cut-off values for the new Alt_MS_Z-score



Alt_MS_Z-score cut-off values:

> 3.10 = non-failed schemes

1.5 to 3.10 = grey zone

< 1.5 = failed schemes

The Z_2 in the Altman model was ≤ 1.23 and ≥ 2.9 for failed and non-failed schemes respectively, which is very close to the above observations.

5. Discussion

The MDA technique commonly has its application in clinical and biological studies where matching the characteristics of the two groups under study is always an important part of the exercise, to ensure that no bias is introduced by a significant difference in the measurements of the independent variables. It is therefore not clear why Altman did not find it necessary to match the measurement in asset sizes especially when asset size is a denominator in at least four of the variables used in the Z-score. The asset size of a company is its capacity to generate sales; hence asset turnover (sales / assets) has to be an important variable in the model.

Regarding the generalizability of the model, Altman never purported that his model was the ultimate and final version; instead he emphasized the need for re-estimation of ratios in different settings, in order to improve the accuracy of the model. The results could therefore be improved amongst medical schemes once the assumptions are refined and finality reached on where to place the outstanding claims provision and savings liability. Altman should be credited for his work on the approach to failure prediction rather than dwelling on the accuracy of the Z-score. The approach, as described above by Altman (1968), spells out the process in variable selection, which by extension infers that re-estimation and reconstitution of variables and coefficients is a necessity in order to improve the accuracy of the model. Balcean et al, in their study in 2004, concluded as follows on the accuracy rates of all commonly used predictive models: “we may question the benefits to be gained from using the more sophisticated alternative methods”. The more sophisticated alternative models refer to the models more recent to the Altman models. What is important from this study (Balcaen & Ooghe, 2004) though, is that it does not conclude that the MDA or Altman models are inferior or are of no value compared to the newer models. This then allows us to apply the Altman Z_2 with the necessary confidence required particularly since it is also the most practical model to apply on an operational level.

One of the criticisms leveled at the MDA and logit analysis models is that they are cross sectional in nature. They therefore take snap shot views at the circumstances that potentially bankrupt and non-bankrupt companies find themselves in at a particular time period and classify them into either group based on the pre-specified continuum that puts them into a bankrupt, non-bankrupt or indecisive category. Practically, a time series scenario can be created by a serial estimation of the Altman Z-score on a quarterly basis in order to monitor the movement of the score from the healthy to distressed range.

The theoretical issues around these models are unlikely to be resolved amongst researchers as there are now a myriad of new models with new theoretical bases. It is expected that the contestation for the "theoretically all inclusive and superior predictive model" will continue for a long time. Each study will take its natural course in that other researchers who are convinced of the theoretical basis of a model will want to validate it to their own circumstances, in order to find practicability in the model. This study has done just that with the Altman Z_2 by attempting to validate its applicability in the medical scheme industry in South Africa, based on the theoretical assumptions of Altman (1968).

The Altman models, with the theoretically sound backing they enjoy, are perhaps as relevant today as they were during their inception in the 1960's. It can be concluded with certainty that the model is still as relevant today as it was in the 1960's.

5.1. Comparing variables of failed and non-failed schemes

In the Altman MDA model, all variables except the T5 showed statistically significant differences between failed and non-failed companies. Altman nonetheless included T5 because it had a higher co-efficient (i.e. carrying more weight). There is no statistically significant difference in the T1 (working capital / total assets) of the failed and the non-failed schemes in the overall and open schemes. This observation could be because all schemes (failed and non-failed) generally manage their cash cycles poorly. This reality is borne out by the fact that schemes pay hospitals much sooner in return for discounts on claims payment. There have been no studies validating that these discounts adequately compensate for the reduction in cash flows. This practice does not have any sound finance theoretical basis, as shortening the cash cycle reduces schemes' cash flows.

The fact that the independent variables are financial ratios, allows managers not only to understand the contributory strength of the variables but assist them to possibly work out the origins of the failure from a managerial perspective. This has significant company "turn around success" implication.

Further studies are necessary to elucidate the above phenomenon: such as why there is no statistically significant difference between the asset turnovers of the failed and non-failed schemes.

5.2. Correlation of variables with the Z-score

In general, there was a significant correlation between the earnings and equity/ debt ratio (T2, T3 and T4) and the Z-score in all the schemes, whilst there was a strong correlation between equity/debt ratio and asset turn over (T4 and T5) with the Z-score in all non-failed schemes (overall, open and restrictive). The significance of sales or efficient use of assets in achieving sales seems to be a significant driver of the Z-value in non-failed schemes. This suggests that significant investment in business development is a key strategic consideration and differentiator between failed and non-failed schemes. This was true even for open schemes where an additional differentiator was poor working capital management in failed schemes (correlation between T1 and T5). Very interesting to note is the negative correlation between sales and equity (sales / total assets and equity / total sales), suggesting that these schemes either had negative sales or were destroying value in the attempt to increase sales resulting in negative cash flows.

5.3. Performance of the MDA model in the SA Medical scheme industry

The accuracy of the Altman model was calculated under two scenarios, first with grey zone counts included and secondly with grey zone counts excluded.

5.3.1. Classification and error rates with grey zone counts included

The results of the calculations including the grey zone counts show poor outcomes as expected. The general trend for all schemes, one and two years prior to failure, show an average predictive value of 60% and above, with an average combined error rate (Type I and Type II errors) of around 10%; except in years 2003/2004 and 2004/2005 for one year and two years prior to failure (respectively) where the predictive values are both 48%. Restricted schemes generally performed better than open schemes in both predictive values and error rates.

5.3.2. Classification and error rates with grey zone counts excluded

This methodology of excluding the grey zone counts is the preferred one as explained above (section 3.5.1. p51). The accuracy rates are much more superior when the grey zone counts have been excluded. The average classification rates in the period 2003 to 2011 are as follows: 82% accuracy rate and 17.9% error rate. The linear trend line inserted in the graph shows the accuracy improving from 72% to 91% between the period 2003/2004 to 2011/2012.

This outcome is consistent with the conclusion in previous studies (Aziz and Humayon, 2006: 27) that showed the accuracy rates in most failure prediction studies to be as follows: 84%, 88%, and 85% for statistical models, AEIS models and theoretical models respectively.

An anomaly was observed in the year 2005/2006 where the accuracy and error rates are 45% and 55% respectively and 46% and 54% respectively for two years and one year prior to failure respectively. The savings options were introduced in 2005 which could be one of the reasons for the inconsistency of the model over this period. Further studies are required to elucidate the introduction of savings and the accuracy rate in that period.

5.3.3 The new and alternative Z-scores

The exercise of establishing new and alternative Z-scores was performed in order to complete the understanding of the Altman prediction failure model in the context of the South African medical schemes. Hence the considerable effort put into this study to better understand the process of co-efficient re-estimation and variable selection.

It is encouraging to note that the cut-offs points of Alt_MS_Z-score compares favorably with the revised Altman Z-score cut-offs:

> 3.10 = non-failed schemes

1.5 to 3.10 = grey zone

< 1.5 = failed schemes

These values are very close to the Altman model (private firms) cut off values of ≤ 1.23 and ≥ 2.9 for failed and non-failed schemes respectively

The rest of the results are otherwise disappointing for the following reasons:

- Both the new and Alternative Z equations resulted in unexplained negative coefficients for some of the variables:

  New_MS_ Z= -1.77T1 - 0.3123T2 -1.733T3 - 0.031T4 + 0.283T5

$$Alt\_MS\_Z = -1.03T1 + 0.034T4 + 0.504T5 - 4.467c - 2.70d + 3.93b$$

- There is a much better classification accuracy in classifying non-failed schemes than in classifying failed schemes

The practical implication of the above observation is not immediately apparent.

The following observations are encouraging for further studies in the exercise of establishing new and alternative Z-scores amongst SA medical schemes:

- The probability plots of both MS_Z_scores and Alt_MS_Z-scores are sigmoid in shape which serves as a reasonability check.
- The medians of both MS_Z_values and Alt_MS_Z values for failed and non-failed schemes are statistically significant.

6. Conclusion

This study has achieved the objective of validating the potential application of the Altman failure prediction models in the medical scheme industry and the Altman prediction failure model has been validated amongst the South African medical schemes. The validation is based on the following outcomes:

- The average classification rates in the period 2002 to 2011 are as follows: 82% accuracy rate and 17.9% error rate, consistent with most statistical MDA failure prediction models.
- There is a statistical difference between the medians of the Z-scores of the failed and non-failed schemes.
- There are different key drivers for the Z-values of failed and non-failed schemes.
- There are statistical differences between the medians of most of the variables (T2, T3, and T4) of the failed and non-failed schemes
- The model is compliant to a number of reasonability checks; such as correlation between T1 and T2 and
- The model has compliance probability curves.

The benefit of the study is that it has created a deeper understanding of the Altman model which paves the way for further studies in the area.

The nature of the medical scheme sector is such that it presents practical and technical difficulties in the application of the model.

Further studies are required to test the rest of the study objectives under conditions where some of the assumptions are revised.

The impact of the introduction of the savings options, since 2005, needs to be better understood and elucidated.

7. ABREVIATIONS

AIES	Artificially intelligent expert system
ARV	Antiretroviral
BOT	Board of Trustees
GEMS	Government Employee Medical Schemes
GFAs	Generic Failure Agents
HIV/AIDS	Human Immunodeficiency Virus / Acquired Immunodeficiency Disease
LDA	Linear discriminate analysis
MDA	Multivariate discriminate analysis
MDGs	Millennium Development Goals
NHI	National Health Insurance
OPA	Overall Predictive Accuracy
PMB	Prescribed Minimal Benefit
PO	Principal Officer
SA	South Africa
SCAs	Sub-causal Agents
SEP	Single Exit Pricing
T1	Working capital / total assets
T2	Retain earnings / total assets
T3	Earnings before interest and taxes / total assets
T4	Market value of equity / book values of total liabilities
T5	Sales / total assets
TB	Tuberculosis
US	United States
Z	Overall index
Z2	Overall index for private firms

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9. ANNEXURES

9.1. Annexure A

List of all failed schemes in order of the year they were registered.

Name of Medical Scheme	Type	Year Began	Year Failed
Vulamed Medical Aid Society	OPEN	2002/2003	2002/2003
Pretoria Municipal Medical Aid (PRETMED)	OPEN	2002/2003	2003/2004
AllCare Chamber Medical Aid Scheme	OPEN	2002/2003	2003/2004
Visimed Medical Scheme	OPEN	2002/2003	2004/2005
Omnihealth	OPEN	2002/2003	2005/2006
Medical Expenses Distribution Society (MEDS)	OPEN	2002/2003	2005/2006
Free State Medical Aid Scheme	OPEN	2002/2003	2005/2006
Protector Health	OPEN	2002/2003	2006/2007
Meridian Health	OPEN	2002/2003	2007/2008
Commercial and Industrial Medical Aid Society (CIMAS)	OPEN	2002/2003	2007/2008
Global Health	OPEN	2002/2003	2007/2008
Lifemed Medical Scheme	OPEN	2002/2003	2007/2008
KwaZulu-Natal Medical Aid Scheme	OPEN	2002/2003	2008/2009
MethealthOpenplan Medical Scheme	OPEN	2002/2003	2008/2009
X-Press Care Medical Scheme	OPEN	2002/2003	2008/2009
Pathfinder Medical Scheme	OPEN	2002/2003	2008/2009
Telemed	OPEN	2002/2003	2009/2010
NBC Medical Scheme	OPEN	2002/2003	2009/2010
Medicover 2000	OPEN	2002/2003	2009/2010
Caremed Medical Scheme	OPEN	2002/2003	2010/2011
Gen-Health Medical Scheme	OPEN	2002/2003	2010/2011
Ingwe Health Plan	OPEN	2002/2003	2010/2011
Pulz Medical Scheme	OPEN	2003/2004	2004/2005
Baymed	OPEN	2004/2005	2006/2007
Eclipse Medical Scheme	OPEN	2004/2005	2006/2007
KPMG Medical Aid Society	RESTRICTED	2002/2003	2002/2003
Ammosal Benefit Society	RESTRICTED	2002/2003	2002/2003
Independent Newspapers Medical Aid Scheme	RESTRICTED	2002/2003	2002/2003
NBS/BOE Group Medical Aid Fund	RESTRICTED	2002/2003	2002/2003
Da Gama Medical Scheme	RESTRICTED	2002/2003	2002/2003
Universal Medical Scheme	RESTRICTED	2002/2003	2002/2003
Aumed Medical Aid Scheme	RESTRICTED	2002/2003	2002/2003
Jomed Medical Scheme	RESTRICTED	2002/2003	2003/2004
Highveld Medical Scheme	RESTRICTED	2002/2003	2003/2004
Billmed Medical Scheme	RESTRICTED	2002/2003	2004/2005
Anglogold Medical Scheme (Goldmed)	RESTRICTED	2002/2003	2004/2005
ABI Medical Aid Scheme	RESTRICTED	2002/2003	2004/2005
G5Med	RESTRICTED	2002/2003	2005/2006
Venda Police and Prisons Medical Scheme (Polprismed)	RESTRICTED	2002/2003	2005/2006
Klerksdorp Medical Benefit Scheme (KDM)	RESTRICTED	2002/2003	2006/2007
Mutual & Federal Medical Aid Fund	RESTRICTED	2002/2003	2007/2008
Ellerines Holdings Medical Aid Society	RESTRICTED	2002/2003	2007/2008
CSIR Medical Scheme	RESTRICTED	2002/2003	2007/2008
Chamber of Mines Medical Aid Society	RESTRICTED	2002/2003	2008/2009
Johannesburg Metropolitan Chamber of Commerce and Industry Medical Aid Society	RESTRICTED	2002/2003	2008/2009
Cawmed Medical Scheme	RESTRICTED	2002/2003	2008/2009
Samancor Health Plan	RESTRICTED	2002/2003	2008/2009
Stocksmed	RESTRICTED	2002/2003	2009/2010
Alliance Midmed Medical Scheme	RESTRICTED	2002/2003	2009/2010
MEDCOR	RESTRICTED	2002/2003	2009/2010
Umed	RESTRICTED	2002/2003	2010/2011
Alpha Group Medical Scheme	RESTRICTED	2002/2003	2010/2011
Clicks Group Medical Scheme	RESTRICTED	2002/2003	2010/2011
Built Environment Professional Associations Medical Scheme (BEPS)	RESTRICTED	2003/2004	2010/2011
Solvita Medical Scheme	RESTRICTED	2008/2009	2009/2010

9.2. Annexure B

The following tables are comparisons of the medians of the variables (T1 to T5) and Z-scores of failed and non-failed schemes (open and restricted), using the Mann-Whitney test in the period 2002/2003 to 2011/2012.

Non-Failed Schemes									
Type	**Variable**	**N**	**Min**	**Max**	**Mean**	**Std Dev.**	**Median**	**25th Percentile**	**75th Percentile**
Open	**T1**	26	-0.08	0.10	-0.01	0.05	-0.01	-0.04	0.02
	T2	26	-0.42	0.74	0.09	0.19	0.05	0.02	0.12
	T3	26	-0.51	0.36	0.00	0.14	-0.01	-0.03	0.06
	T4	25	1.49	19.94	5.72	4.92	3.83	2.40	6.80
	T5	26	0.05	160.13	16.53	35.91	3.85	1.25	5.56
Restricted	**T1**	71	-0.14	0.12	-0.01	0.05	-0.01	-0.04	0.01
	T2	71	-0.12	0.48	0.07	0.10	0.06	0.01	0.12
	T3	71	-0.59	0.45	0.00	0.13	0.01	-0.06	0.08
	T4	70	0.27	69.60	11.57	11.53	7.62	3.76	15.87
	T5	71	0.01	893.01	18.94	105.82	1.97	0.66	7.04
Total	**T1**	97	-0.14	0.12	-0.01	0.05	-0.01	-0.04	0.01
	T2	97	-0.42	0.74	0.08	0.13	0.06	0.02	0.12
	T3	97	-0.59	0.45	0.00	0.13	0.00	-0.05	0.07
	T4	95	0.27	69.60	10.03	10.51	5.78	3.21	14.04
	T5	97	0.01	893.01	18.29	92.21	2.30	0.87	6.17

Failed Schemes									
Type	**Variable**	**N**	**Min**	**Max**	**Mean**	**Std Dev.**	**Median**	**25th Percentile**	**75th Percentile**
Open	**T1**	15	-4.24	0.49	-0.29	1.11	0.00	-0.11	0.02
	T2	15	-4.06	0.23	-0.33	1.08	-0.01	-0.11	0.12
	T3	15	-4.07	0.21	-0.40	1.08	-0.09	-0.18	0.07
	T4	15	-5.87	27.67	3.28	7.38	1.50	0.35	4.05
	T5	15	0.31	13.91	3.62	3.93	2.22	1.31	4.15
Restricted	**T1**	15	-0.06	0.21	0.03	0.06	0.02	0.00	0.05
	T2	16	-0.63	0.25	0.01	0.20	0.02	-0.04	0.15
	T3	16	-0.75	0.21	-0.09	0.24	-0.03	-0.12	0.01
	T4	14	0.16	26.17	5.94	7.45	2.37	1.77	6.75
	T5	15	0.00	4.80	1.20	1.19	0.80	0.73	1.09
Total	**T1**	30	-4.24	0.49	-0.13	0.79	0.00	-0.03	0.04
	T2	31	-4.06	0.25	-0.15	0.77	0.00	-0.09	0.12
	T3	31	-4.07	0.21	-0.24	0.77	-0.05	-0.15	0.03
	T4	29	-5.87	27.67	4.56	7.40	2.09	0.82	4.58
	T5	30	0.00	13.91	2.41	3.11	1.20	0.75	3.03

9.3. Annexure C

The table below illustrates classification and error rates as well as percentage of unclassifiable schemes

Actual Year	Prediction(years prior to failure)	Type of scheme	Classified Companies		Unable to classify
			Classification Rate	**Error rate**	
2003/2004	2	All Schemes	NA	NA	NA
		Open	NA	NA	NA
		Restricted	NA	NA	NA
	1	All Schemes	84%	16%	43%
		Open	81%	19%	66%
		Restricted	85%	15%	30%
2004/2005	2	All Schemes	84%	16%	43%
		Open	80%	20%	67%
		Restricted	84%	16%	29%
	1	All Schemes	92%	8%	4%
		Open	87%	13%	0%
		Restricted	95%	5%	6%
2005/2006	2	All Schemes	45%	55%	4%
		Open	81%	19%	0%
		Restricted	95%	5%	6%
	1	All Schemes	46%	54%	10%
		Open	82%	18%	6%
		Restricted	93%	7%	12%
2006/2007	2	All Schemes	86%	14%	11%
		Open	80%	20%	7%
		Restricted	90%	10%	13%
	1	All Schemes	83%	17%	28%
		Open	78%	22%	26%
		Restricted	86%	14%	29%
2007/2008	2	All Schemes	83%	17%	28%
		Open	80%	20%	27%
		Restricted	84%	16%	28%
	1	All Schemes	88%	12%	31%
		Open	85%	15%	10%
		Restricted	90%	10%	29%
2008/2009	2	All Schemes	88%	12%	30%
		Open	88%	13%	33%
		Restricted	88%	12%	28%
	1	All Schemes	84%	16%	26%
		Open	79%	21%	22%
		Restricted	86%	14%	28%
2009/2010	2	All Schemes	86%	14%	27%
		Open	80%	20%	24%
		Restricted	89%	11%	28%
	1	All Schemes	85%	15%	30%
		Open	80%	20%	35%
		Restricted	87%	13%	27%
2010/2011	2	All Schemes	89%	11%	28%
		Open	89%	11%	36%
		Restricted	89%	11%	25%
	1	All Schemes	87%	13%	27%
		Open	88%	13%	20%
		Restricted	86%	14%	30%
2011/2012	2	All Schemes	93%	7%	28%
		Open	96%	5%	22%
		Restricted	92%	8%	30%
	1	All Schemes	93%	7%	21%
		Open	95%	5%	15%
		Restricted	93%	7%	23%

9.4. Annexure D

This annexure shows the re-substitution and leave-one-out classifications and posterior probabilities for those observations that were misclassified by the LDA model.

Obs	Classification			Probabilities		LOO Probabilities	
	TRUE	Class	LOO Cl.	0	1	0	1
1	1	0 *	0 *	0.5571	0.4429	0.5881	0.4119
3	1	0 *	0 *	0.7244	0.2756	0.7698	0.2302
4	1	0 *	0 *	0.6974	0.3026	0.7177	0.2823
5	1	0 *	0 *	0.7948	0.2052	0.8479	0.1521
7	1	0 *	0 *	0.6258	0.3742	0.6526	0.3474
10	1	0 *	0 *	0.6273	0.3727	0.6484	0.3516
13	1	0 *	0 *	0.5443	0.4557	0.5764	0.4236
15	1	1	0 *	0.4513	0.5487	0.53	0.47
16	1	0 *	0 *	0.5802	0.4198	0.5924	0.4076
17	1	0 *	0 *	0.6294	0.3706	0.6413	0.3587
19	1	0 *	0 *	0.561	0.439	0.5815	0.4185
20	1	0 *	0 *	0.5798	0.4202	0.5998	0.4002
22	1	0 *	0 *	0.6055	0.3945	0.6269	0.3731
23	1	0 *	0 *	0.5993	0.4007	0.6156	0.3844
25	1	0 *	0 *	0.5891	0.4109	0.6311	0.3689
26	1	0 *	0 *	0.5584	0.4416	0.5627	0.4373
28	1	0 *	0 *	0.5308	0.4692	0.5427	0.4573
29	1	0 *	0 *	0.6287	0.3713	0.6478	0.3522
31	1	0 *	0 *	0.5092	0.4908	0.52	0.48
32	1	0 *	0 *	0.6948	0.3052	0.7152	0.2848
34	1	0 *	0 *	0.5512	0.4488	0.6029	0.3971
51	0	1 *	1 *	0.391	0.609	0.3801	0.6199
54	0	1 *	1 *	0.4514	0.5486	0.4293	0.5707
57	0	1 *	1 *	0.4529	0.5471	0.4435	0.5565
58	0	1 *	1 *	0.4908	0.5092	0.4837	0.5163
62	0	1 *	1 *	0.0801	0.9199	0.0256	0.9744
72	0	1 *	1 *	0.4082	0.5918	0.0802	0.9198
77	0	1 *	1 *	0.4702	0.5298	0.4684	0.5316
82	0	1 *	1 *	0.4844	0.5156	0.4811	0.5189
98	0	1 *	1 *	0.4601	0.5399	0.4529	0.5471
100	0	1 *	1 *	0.4648	0.5352	0.4302	0.5698
102	0	1 *	1 *	0.3553	0.6447	0.3446	0.6554
103	0	1 *	1 *	0.374	0.626	0.3285	0.6715
105	0	1 *	1 *	0.4338	0.5662	0.4254	0.5746
109	0	1 *	1 *	0.466	0.534	0.4606	0.5394
112	0	1 *	1 *	0.485	0.515	0.4455	0.5545
115	0	1 *	1 *	0.4275	0.5725	0.418	0.582
118	0	1 *	1 *	0.199	0.801	0.178	0.822
119	0	1 *	1 *	0.4566	0.5434	0.4337	0.5663

9.5. Annexure E

This annexure shows the re-substitution and leave-one-out classifications and posterior probabilities for those observations that were misclassified by the LDA model whilst re-establishing the Alt_MS_Z-score.

Obs	Classification			Probabilities		LOO Probabilities	
	TRUE	Class	LOO Cl.	0	1	0	1
1	1	1	0 *	0.4996	0.5004	0.5266	0.4734
3	1	0 *	0 *	0.8104	0.1896	0.9534	0.0466
4	1	0 *	0 *	0.549	0.451	0.5834	0.4166
5	1	0 *	0 *	0.9548	0.0452	0.9798	0.0202
10	1	0 *	0 *	0.6844	0.3156	0.7089	0.2911
17	1	0 *	0 *	0.8427	0.1573	0.865	0.135
20	1	0 *	0 *	0.5772	0.4228	0.6019	0.3981
22	1	0 *	0 *	0.6086	0.3914	0.6411	0.3589
23	1	0 *	0 *	0.6965	0.3035	0.7226	0.2774
24	1	0 *	0 *	0.5547	0.4453	0.5721	0.4279
26	1	0 *	0 *	0.5631	0.4369	0.5733	0.4267
28	1	0 *	0 *	0.65	0.35	0.6712	0.3288
29	1	0 *	0 *	0.6921	0.3079	0.7202	0.2798
30	1	0 *	0 *	0.5774	0.4226	0.5979	0.4021
32	1	0 *	0 *	0.7078	0.2922	0.7346	0.2654
34	1	0 *	0 *	0.6124	0.3876	0.7133	0.2867
35	1	0 *	0 *	0.5245	0.4755	0.5404	0.4596
38	1	0 *	0 *	0.5614	0.4386	0.5757	0.4243
51	0	1 *	1 *	0.4239	0.5761	0.4112	0.5888
54	0	0	1 *	0.508	0.492	0.4887	0.5113
60	0	1 *	1 *	0.4966	0.5034	0.4431	0.5569
62	0	1 *	1 *	0.1036	0.8964	0.0502	0.9498
70	0	1 *	1 *	0.142	0.858	0.1057	0.8943
72	0	1 *	1 *	0.1855	0.8145	0.0554	0.9446
78	0	1 *	1 *	0.3352	0.6648	0.3036	0.6964
98	0	1 *	1 *	0.3867	0.6133	0.3717	0.6283
100	0	1 *	1 *	0.4105	0.5895	0.3927	0.6073
102	0	1 *	1 *	0.4316	0.5684	0.4208	0.5792
103	0	0	1 *	0.5016	0.4984	0.4906	0.5094
112	0	1 *	1 *	0.4415	0.5585	0.424	0.576
115	0	1 *	1 *	0.4894	0.5106	0.4822	0.5178
118	0	1 *	1 *	0.2938	0.7062	0.2774	0.7226
119	0	0	1 *	0.5069	0.4931	0.4793	0.5207